A systematic approach of integrated building control for optimization of energy and cost

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Abstract

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More efficient building energy management leads to lower energy consumption and cost, higher occupancy comfort and less detrimental effects on the environment. Improving building energy management with advanced integrated building control provides a tool to coordinate and optimize control of multiple indoor parameters by considering their interconnected effects on building energy consumption and comfort.

A building integrated optimization requires an approach to calculate building energy consumption, operate in real time, optimize building control parameters, and be able to modify systems operations or schedules in response to environmental or demand response signals inputs. The integrated optimization has significant effects on reductions in energy use and energy costs, reductions in peak load, and improvement of indoor environment quality without replacing the existing equipment. Most of previous research in integrated building control just focused on optimization of specific zone or some of the possible parameters. They also applied their optimization for the current hour without considering its effect on future-hours.

The main goal of this research is to develop an advanced building operation optimization tool for integrated control of lighting, shade, ventilation and heating and cooling systems for whole buildings to reduce building energy consumption, operation cost, and peak load while satisfying occupancy comfort. Also, this optimization tool is capable of coordinating integrated control and demand response by real-time modification of time-of-use prices that are received from utilities. In addition, it applies multi-hour optimization by optimizing several hours simultaneously and considering effects of current hour control parameters on future hour energy consumption.

As a first step, integrated optimization is investigated based on a developed and validated RC-network model of a typical small office building. Nonlinear optimization is applied to the RC-network model that is created in MATLAB. The optimization results show energy savings up to

35% more than the scheduled control. In addition, multi-hour optimization saved up to 4% of energy cost compare to optimization based on the current hour.

For more accurate building energy and cost calculation, using building simulation software is essential. In this research DOE-2 is chosen as an open source building energy use analysis tool and modified based on integrated optimization requirements by adding functions to DOE-2 source code. DOE-2 requires modifications to accept the control parameters' online and hourly bases. Accomplished modification is validated by simulating nighttime ventilation strategy. Also, the daylighting and window energy calculation algorithm is modified to operate based on shade position instead of just open or closed shade.

A building-integrated optimization tool is developed by integrating the genetic algorithm optimization method in MATLAB with building energy and cost calculation software (DOE-2). This integrated optimization tool simulates and optimizes building control parameters such as indoor temperatures, shade position, artificial light power, and outdoor air ventilation rates for an entire building. This optimization tool can be easy applied to any type of building and system when their models are available in DOE-2. Moreover, different strategies are proposed for increasing speed of optimization. First, a rule-based decision-making tool is used before integrated optimization that modifies the control parameters optimization domain. Decision-making rules are developed based on sample integrated optimization results. Second, the neural network is trained for energy consumption prediction of building based on energy consumption results from DOE-2 for random control parameters. This trained neural network is connected to a genetic algorithm and replaces DOE-2 for the energy consumption calculation. Finally, a local optimization method is used after the genetic algorithm to search around genetic algorithm results of control parameters for new control parameters with lower building energy consumption.

The integrated MATLAB and DOE-2 optimization tool is initially evaluated by investigating nighttime ventilation and shade position optimization. The results for nighttime ventilation optimization show total energy savings up to 8% and cooling energy consumption reduction up to 23%. Higher savings occurred on days with high diurnal temperature range and average outdoor temperature near 17 ˚C. The results for shade position optimization indicate that in hot days shades stay nearly closed since the effect of solar heat gain, which increases cooling energy consumption in addition to the detrimental effect of conduction heat transfer, is more effective and important than lighting energy reduction from daylighting. Also, in transient seasons when the building is in heating mode, shades mostly stay open since heat gain and illuminance transmission from windows reduce both heating and lighting energy consumption. In addition, using thick shades and a lower illuminance set-point give optimization more flexibility for energy savings.

Finally the integrated MATLAB and DOE-2 optimization tool for whole building energy optimization is applied to a typical office building in Montreal. The results show energy savings between 10% and 30%; also higher energy savings potential could be expected during transient seasons compared to very hot or very cold seasons. The results also show peak load savings up to 40%.

Keywords: building model, energy consumption, integrated control, optimization, DOE-2

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Nomenclature

Symbol	**Description**
DR	Demand response
GHG	Greenhouse gas
HVAC	Heating, ventilation and air-conditioning
EMCS	Energy management and control system
IAQ	Indoor air quality
NN	Neural networks
LP	Linear programming
NLP	Nonlinear programming
GA	Genetic algorithms
PSO	Particle swarm optimization
V	Volume (m^3)
ρ	Density (kg/m^3)
C	Average specific heat (J/kgK)
T	Temperature (°C)
q	Energy rate (W)
A	Area (m^2)
H	Heat transfer coefficient (W/m^2K)
$\dot{m}$	mass flow rate (kg/s)
R	Thermal resistance (Km^2/W)
k	Thermal conductivity (W/mK)
E	Energy consumption (kJ)
x	Control variables
η	Performance coefficient
EP	Electricity price
GP	Gas price

Subscript	**Description**
Z	Zone number
I	Optimization hour
Min	Minimum
Max	Maximum
Ave	Average

1 Introduction

1.1 Building energy consumption

Energy consumption in the commercial and institutional building sector accounts for almost 17% of total energy use in Canada and almost 13% of the country's greenhouse gas (GHG) emissions, approximately 60 Mt of CO_2 equivalents in 2006 [1]. The inefficient consumption of energy has more detrimental effects on the natural environment. The environmental damage from particulate pollution, acid rain, and climate change, all resulting from burning fossil fuel, has been documented extensively in many publications (e.g., [2]). The need to reduce the environmental impact of buildings is clear, particularly through reducing their wasteful use of energy.

In Canada 76% of energy used by building services (e.g., heating, cooling, lighting, etc.) are powered by electricity, accounting for 35% of the total electricity consumed nationally [3]. Heating, ventilation and air-conditioning (HVAC) systems in commercial buildings account for nearly 80% of the total building energy.

1.2 Making our buildings smart and intelligent with integrated control

Building energy consumption can be improved by using efficient systems and operating them efficiently, through better control. "Intelligent efficiency" is defined by the American Council for an Energy-Efficient Economy (ACEEE) in 2012 [4] as "a systems-based, holistic approach to energy savings, enabled by information and communication technology and user access to real-time information. Intelligent efficiency differs from component energy efficiency in that it is adaptive, anticipatory, and networked." Generally the word "smart" is used for equipment, appliances, or networks with ability to communicate information, and changing their control parameters for better efficiency based on this information. Smart buildings have sensors and controls that communicate with a central building automation system. Intelligent efficiency includes an approach in which system-wide energy savings can be achieved by coordinating operations of interconnected devices. Integrated building control optimization, which coordinates multiple demand-side control parameters, can offer a more advanced approach to building energy management for higher cost-effective savings and control opportunities, while increasing occupant comfort.

An effective smart integrated building control typically has the following characteristics: evaluate and calculates building energy consumption in some methods, operates in real time, is capable of understand relevant control parameters (e.g., building operation and occupancy), and is able to change systems operations or scheduling in response to inputs. In order to optimally control system energy use and cost, a smart controller could understand and consider any of the following inputs.

Outdoor air conditions: Outdoor air temperature, air quality, and solar illuminance and heat gain can affect building load and lighting. Hence knowing outdoor conditions can help to optimize building energy consumption more efficiently.

Utility rates: The cost of each unit of energy may vary, for example, because of time-of-use rates. Therefore, it may be optimal to shift the systems operation away from high-cost periods. This can be done using both current and anticipated rates.

Occupancy: Limiting pollutant levels, narrow temperature set-point, and higher lighting levels are only necessary when a space is occupied. Knowing when the space is or is not occupied can help reduce the amount of necessary energy compare to when it is occupied.

1.3 Integrated control potential

According to Brambley's market surveys [5], building controls can potentially reduce energy consumption significantly in commercial buildings. Brambley's survey demonstrates how a traditional Energy Management and Control System (EMCS) can save between 5 and 15% of a building's energy, or occupancy sensors for lighting control can save 20 to 28% energy, or demand controlled ventilation can lead to 10–15% energy savings. In addition, controlling HVAC systems to improve temperature control and provide thermal comfort for occupants has significant effects on the building energy consumption, without replacing the existing (less efficient) with new (more efficient) equipment.

A building's electromechanical systems operation is critical to optimizing energy use, reducing energy and maintenance costs, ensuring occupant comfort and maintaining the quality of indoor air. Today's buildings are complex and have interdependent systems with sophisticated controls (such as fuzzy logic, adaptive and predictive controls). Optimizing a building's energy consumption requires an approach that allows devices and systems to work together in an efficient and cost-effective way to meet occupant requirements and expectations. Many case studies have shown an integrated control opportunity for significant energy savings ([6–8]).

Another advantage of an advanced building control system is flexibility to participate in utility-initiated demand-response (DR) programs. DR manages customer consumption of electricity in response to supply conditions. DR strategies focus on controlling an entire building instead of specific parts. Such strategies include demand limiting or demand shifting and shedding.

Smart integrated control could provide the following benefits to building occupants, utility companies, and efficiency program managers: (1) reductions in energy use and energy costs, (2) improvement of indoor environment quality, (3) reductions in peak load (or equivalently time-of-use pricing), (4) ability to respond to demand response events, (5) flexibility that allows a wide variety of goals to be implemented on one platform, without expensive hardware/equipment changes, and (6) a platform that simplifies future adjustments to control algorithms in response to ongoing changes in climate, regulation, energy prices, grid dynamics, or occupant behavior.

1.4 Integrated control versus typical local control

Typical control functions in buildings can be divided into two categories: local control and supervisory control. Local control provides basic control and automation functions, such as ON/OFF control and proportional-integral-derivative (PID) control that allows building services to operate properly. Several studies have shown that local controls can provide thermal comfort and satisfy goals for indoor air quality without significant effect on energy savings [9–11]. Supervisory control functions are higher level controls that include local control functions while considering whole system characteristics and operations interaction, and energy optimization for total building energy use. During the last decade, research has increasingly focused on supervisory control, primarily caused by higher energy prices and tighter energy supply.

Many buildings have multiple systems that typically work independent of each other. These systems include heating, cooling, lighting, ventilation, automated blinds, and domestic hot water. The control strategies of existing building systems are mostly based on an open-loop controller or predefined relation between parameters. These control methods lead to poor energy management and comfort [5]. In addition these methods require significant effort during installation and continuous adaptation of control parameters in order to provide acceptable energy management and environmental comfort. Most advanced building energy management systems do not work at their fullest potential. Usually they are just used for applying fixed schedules to the operation of the systems or individual control of each system. As an example, typical ventilation controls are usually met by continuous ventilation for the whole building without considering demand. Lower HVAC power and energy consumption and higher indoor air quality (IAQ) performance can be achieved by being smarter about using ventilation. High-performance buildings can take advantage of smart ventilation strategies, such as increasing ventilation when the outdoor temperature is less extreme, increasing ventilation during off-peak hours, managing ventilation based on outdoor air quality, and reducing whole-building ventilation operation in response to occupancy and building situations [12].

Parameters that influence indoor environment quality such as temperature, humidity, CO_2 concentration, and lighting can be adjusted optimally through operating integrated control instead of separate controllers. Furthermore, it is not easy to obtain the right combinations of values of these parameters since operating a single device might have several effects on building environment comfort parameters. As an example, bringing in fresh air for reducing CO_2 concentration can affect inside temperature and humidity. As a result in terms of total performance, individual and independent control systems do not usually work in an optimal manner. Instead, integrated control systems have the potential to improve energy efficiency, occupant comfort and cost efficiency. Integrated building control connects the operation of various local controls through a computerized supervisory monitoring and control system.

For an accurate integrated control, information from different parameters and communication between controller device, plant, and building management are necessary. The zone level information required includes: illuminance, glare, occupancy, inside temperature and humidity, and air quality. The plant-level parameters for an integrated control include control parameters of air handling unit controller, chiller controller, and boiler controller. Figure 1-1 shows the relation of zone actuators and goal parameters, also the effect of different systems and parameters on each other.

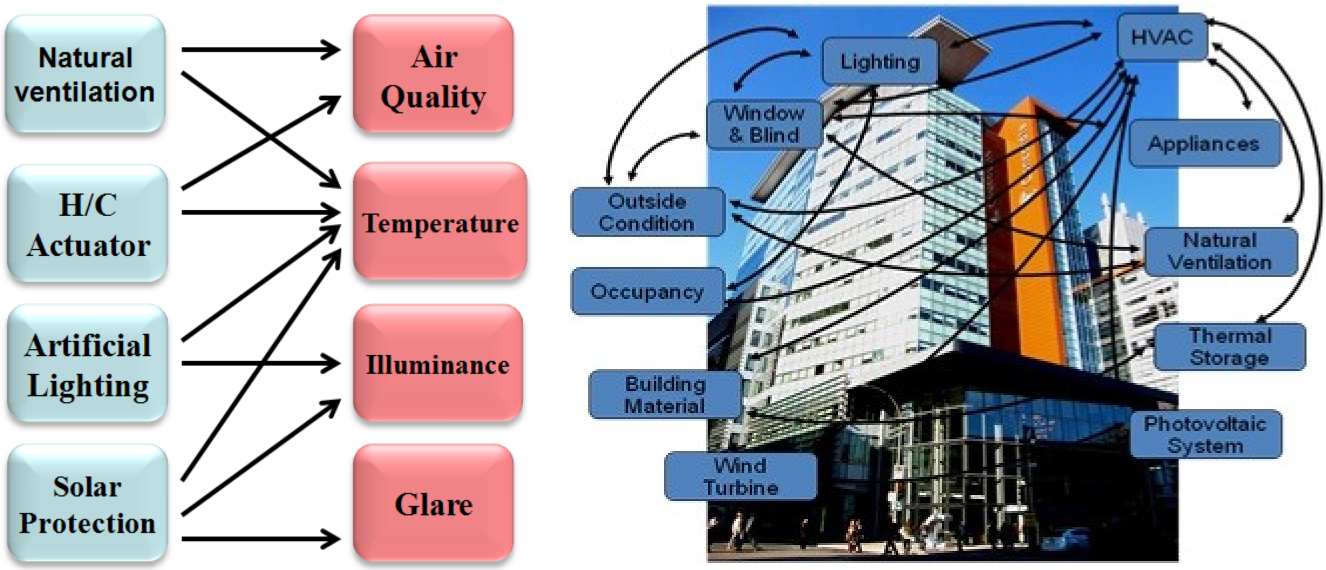


Figure 1-1: (left) Relation of zone actuators and goal parameters, (right) effect of different systems and parameters on each others

1.5 Integrated control applications

Integrated control of the building can be an effective tool in implementing energy efficiency and conservation measures, peak load management, and dynamic demand response to varying electric prices.

Energy efficiency and conservation: Energy efficiency lowers energy use while providing the same level of services. Energy conservation reduces unnecessary energy use. Both energy efficiency and conservation provide environmental protection and utility bill savings. Energy efficiency measures can permanently reduce peak demand by reducing overall consumption. In buildings this is typically done by installing energy-efficient equipment and/or operating buildings efficiently. Integrated building control mostly focuses on energy conservation by reducing energy use with efficient control systems.

Peak Load Management: Peak load management changes the building energy use pattern (load shape) to reduce energy use during peak hours**.** Daily peak load management has been applied in many buildings to minimize the impact of peak demand charges and time-of-use rates.

Smart controls allow us to easily shift the times of energy consumption away from peak demand periods, when loads on the gas and electricity distribution infrastructures reach a maximum. Reducing peak demand benefits both utility companies and consumers, through lower prices and greenhouse gas emissions, as well as increased grid stability and avoidance of service outages.

Demand Response: Demand response (DR) is a dynamic and event-driven strategy that can be defined as short-term modifications in customer end-use electric loads in response to dynamic price and reliability information.

Typical peak load management and demand response methods include load limiting, load shifting, and load shedding. Load limiting refers to dropping loads when predetermined peak load limits are about to be exceeded. This is done to flatten the load shape when the predetermined peak is schedule. Load shifting is shifting the loads from peak periods to off-peak periods. Load shedding is dynamic temporary reduction or curtailment of peak load when dispatched and refers to strategies that can be possibly implemented within a shorter period of response time.

HVAC systems can be an excellent resource for DR for the following reasons. First, HVAC systems include a significant portion of the electric load in commercial buildings. Second, the thermal storage effect of indoor environments allows HVAC systems to be temporarily unloaded without immediate impact on the building occupants. Third, it is common for HVAC systems to be at least partially automated with energy management and control systems (EMCS). Lighting and daylighting can also be effective in reducing peak demand.

1.6 Research objectives

For improvement of energy efficiency and conservation, an optimal operation and control method is developed that reduces all unnecessary energy consumption in the building and optimizes all operation parameters with respect to efficiency of equipment to minimize energy consumption of the building while providing a comfortable environment for occupants. For peak demand management, demand charges and time-of-use rates are considered in the optimization objective function to identify multi-hour control options for the best response to peak load price. Based on the speed of the developed building simulation and optimization technique, the energy use in a building can be simulated each time the building receives new energy price or emergency signals from the utility, to generate a new optimal dynamic response.

The main interest of this research is to develop an advanced building operation system for integrated control of lighting, blinds, ventilation and heating and cooling systems for whole buildings, in order to:

1) Improve the indoor environment (thermal comfort, visual comfort and air quality)
2) Reduce operation cost (energy consumption, energy price and maintenance)

3) Reduce peak load (response to peak demand charge and time-of-use rates)

Also, integrated control and demand response are coordinated, and new rules for whole-building control are created based on optimization results. In addition, a systematic approach to connect optimization method and building energy calculation, as well as, algorithms to increase speed of optimization are introduced.

Although the previous researches introduced earlier tried to control different effective parameters in single or multiple zones, some limitations in those researches (about all possible strategies and effective parameters and methods of optimization) highlight the need for a more accurate and efficient integrated control. Indeed, a building management system should be developed that is able to optimize effective parameters accurately according to current and predicted future building situations in order to reduce building energy consumption and improve the indoor comfort level. Therefore, the objectives of this research are to:

- Develop suitable integrated optimization for whole buildings, in all zones and with all systems
- Consider and model the effect of current hour parameters in future hour energy consumption by multi-hour optimization
- Investigate different objectives for optimization (energy and cost)

To achieve each of these objectives, the desired work steps are:

1. Developing suitable integrated optimization for whole buildings
    1.1. Literature review and parametric simulation for identification of all possible strategies and control parameters
    1.2. Modification of simulation tool (DOE-2), adding specific functions for investigation of all strategies and control parameters
    1.3. Selection of suitable optimization method and finding effective parameters for that optimization method
    1.4. Integration of the simulation tool with the optimization method to develop integrated control optimization with consideration of demand response
    1.5. Investigation of advanced methods for increasing accuracy and speed of optimization
        1.5.1. Developing fuzzy logic rules for recognition of suitable optimization domain according to conditions before simulation and optimization.
        1.5.2. Using neural network between optimization and simulation tools

1.5.3. Using optimization based on building an RC-Network model as an initial point for integrated optimization

2. Multi-hour optimization
    2.1. Finding appropriate effective parameters for an accurate multi-hour optimization
    2.2. Comparing different time steps for multi-hour optimization, and selecting proper time step
3. Different objective functions
    3.1. Adding ability to accept demand response signals as time-of-use price inputs for modification of cost objective function, or using them for modifying optimization constraints
    3.2. Comparing objective function of energy and cost for optimization

Required work steps and objectives of this thesis are investigated and organized in seven chapters. Chapter 2 reviews the majority of the literature related to building integrated control optimization and discusses further opportunities in this field that required more investigation. Chapter 3 investigates methodologies and methods of developing advanced integrated building optimization, which includes methods of modeling the building energy consumption, methods of optimizing building control parameters, and integrating the optimization method with a building energy calculation method, as well as different methods of increasing speed of optimization. Chapter 4 discusses the results of integrated optimization with the RC-networks model and nonlinear programming. Chapter 5 addresses modifications of simulation tools by adding functions to DOE-2 and their applications for nighttime ventilation and shade position. Chapter 6 discusses integration of MATLAB and DOE-2 to develop an optimization tool; the chapter includes different applications of the developed optimization tool and methods of increasing its speed, as well as final results of building energy consumption and cost optimization. Finally chapter 7 presents remarks and conclusions of this thesis, in addition to recommending future works for further investigations.

2 Literature review

The present chapter aims to prepare a complete background of the existing efforts to develop integrated building control and optimization. The optimal control and building energy consumption optimization are investigated with different methods in many studies. For understanding opportunities and potentials in integrated building control, first important and general literatures in this field are discussed. Thereafter, literature with more detail and focus on each method and steps for integrated control are reviewed. Topics of these detailed researches include:

- Building energy and cost calculation methods
- Building optimization techniques
- Important methods for increasing optimization speed and accuracy
- Building load and occupancy prediction
- Including demand response in integrated control

Finally, based on the literature review, unsolved areas that required more investigation are specified and my research objectives are developed based on them.

2.1 Integrated control research opportunities

An intelligent integrated control of building systems can achieve significant energy savings while maintaining a high level of indoor comfort [13]. Most previous work in integrated building control focuses on one zone instead of the whole building, and the authors applied their integrated control to some of the parameters instead of all possible parameters. Mathews et al. [14, 15] and Vakiloroaya et al. [13] focused on HVAC system integration. Daylighting and illuminance control integration was investigated by Pandharipande and Caicedo [16], Shen and Hong [17], Mukherjee et al. [18], and Rubinstein et al. [19]. Roche and Milne [20] investigated the effect of combining smart shading and ventilation; and integrated control of heating, illuminance and daylighting without consideration of air quality was studied by Kolokotsa et al. [8] and Guillemin and Morel [6].

Kolokotsa et al. [8] applied a fuzzy logic algorithm to analyze the performance of an integrated Indoor Environment Energy Management System (IEEMS) for two buildings in Greece. The energy savings achieved by the IEEMS operation is more than 30% compared to the existing control system. The fuzzy controller satisfies the indoor comfort requirements, giving priority to passive techniques for heating, cooling and lighting, while minimizing the energy use.

Gyalistras et al. [21] investigated the energy savings potential of simultaneous control of blinds, electric lighting, heating, cooling and ventilation in a single building zone. They compared whole-year hourly time step simulations with rule-based control and model predictive control for several factors (such as comfort range, air quality controlled ventilation, and façade orientation). The largest energy savings potential was found for the use of CO_2-controlled ventilation (average savings of 13%–28%). A previous study about the impact of shading devices on energy use showed that shading devices reduce the cooling load of building by 23%–89%, with the highest savings attained for devices with low shading coefficient [22].

Karjalainen and Lappalainen [23] provided integrated control for a space and describe various inputs and outputs for integrated controls. The optimization strategy was first simulated and then implemented in a real building. Their simulations showed that more than 20% of the heating energy and the electricity used by ventilation fans could be saved.

Shen et al. [17] used existing simulation tools to compare the energy savings benefits of integrated controls in office buildings. They examined the energy saving benefits of three possible control strategies, combining different strategies in dimming of electric lighting and controllable window transmission (electrochromic windows) compared to a benchmark case across 16 DOE climate zones in the US with EnergyPlus software. Their analysis specified that the current simulation programs could not model sophisticated integrated control strategies.

Guillemin and Morel [6] developed a self-adaptive integrated system for building energy and comfort management. Both artificial and natural lighting controllers were designed in order to fit the integrated approach. They used a genetic algorithm to look for the most efficient set of small variations to the parameters of all controllers for better optimization results. Their experiment results demonstrated that this integrated system can lead to 25% energy savings.

Gwerder and Gyalistras [24] investigated the use of a weather and occupancy forecast for optimal building control. They present a potential savings of both non-predictive and predictive rule-based control for integrated control of one zone. Different rule-based control algorithms were examined and compared in a test field (real scale model of the zone).

Kaya et al. [25] developed an optimal control method for a single air-conditioned zone. The main objective of their study was to demonstrate improvement in control performance and reduction in energy consumption through simultaneous (rather than independent) control of temperature, humidity, and air velocity. The results indicated that the optimal control strategy could reduce energy use.

Sun et al. [26] developed a methodology to get a near-optimal control commands for the blinds, natural ventilation, lights and HVAC system jointly. Numerical simulation results showed that both traditional and integrated strategies can effectively reduce the total energy cost. The integrated control can save more energy than the selected traditional non-integrated control strategies. Their methodology was tested for a fresh-air unit (FAU) of two rooms, but it can be extended to a whole building.

2.2 Building energy and cost calculation methods

Building simulation is an acceptable tool to estimate energy use of a building in response to changes in parameters for complex building and plant dynamics. A simulator is essentially a function evaluator in many optimization systems. Three types of simulation models are common in research: full-scale [27, 28], statistics-based [29, 30], and simplified [31]. EnergyPlus, DOE-2 and BLAST are examples of full-scale system simulation packages. They cover a wide range of building systems and components, take detailed system description, and produce a large number of energy and comfort output reports. A full-scale simulation package can be integrated in the optimization process, but the full-scale simulator would make the optimization process time-consuming and data processing complex. As an alternate method, statistical function approximation is a widely used approach to represent the nonlinear building dynamics. A variety of neural networks (NNs) and time series models have been used in load prediction and control research. In addition, simplified models fall between full-scale simulation and statistical models. They consist of approximate functional relations for components and systems under study, which makes them computationally more efficient than full-scale simulation while providing a fair amount of insight into the energy balance and transfer processes. In this research all of these methods are used to utilize their advantages and compensate for their disadvantages by using the other methods.

2.3 Building optimization techniques

A variety of methods have been applied to building controls and optimization (overviews can be found in [32–34]). Methods proposed for integrated building control include the usage of neural networks [35-37], fuzzy logic approaches [8, 38], rule-based control [21, 24, 39, 40], simulation-based control [13, 17, 23, 41], model predictive control [42, 43], and adaptive control [44, 6].

In order to use optimal control or adaptive control a model of the building is necessary. Predictive control includes a model for prediction of future condition (e.g., solar gains, presence of humans, etc.). This prediction improves thermal comfort mainly by reducing overheating [45–47]. Adaptive controllers have the ability to self-regulate and adapt to the climate conditions or building characteristics in various buildings. In addition, adaptive fuzzy controllers are regarded as the most promising adaptive control systems for buildings [24, 45].

Moreover, a variety of optimization methods have been applied in building control problems, such as linear and non-linear optimization (LP & NLP) [48, 49], genetic algorithm optimization technique [50-52], and dynamic programming (DP) [53]. Linear programming is a mathematical method to optimize an objective function (e.g., maximum gain or minimize cost) subject to a linear convex set of constraints [54]. The linear programming method is an appropriate tool that it is used widely to solve and optimize various types of economic and industrial problems. Therefore, many researchers have applied LP to optimize operation of an integrated building control system.

Petri et al. [55] present a modular-based optimization system efficiently used for running energy simulation and optimization in order to fulfill a number of energy-related objectives. The solution can address the variability in building dynamics and provide support for building managers in implementing energy-efficient optimization plans.

Görkem et al. [56] used the linear programming method to optimize the allocation of limited amount of budget for modification of a household in Turkey in order to maximize the energy savings. The energy conservation measures considered in that study included installing photovoltaic solar cells, replacing regular windows with double-glazed ones, replacing incandescent bulbs with compact fluorescent light bulbs, and replacing household appliances with more efficient appliances. Their results indicated that double-glazed window installation and installing compact fluorescent lights was the optimum combination because of the relative low cost.

Braun [57] studied dynamic building control and dynamic adjustment of the indoor temperature set-points in order to minimize overall operating costs by applying dynamic optimization techniques to computer simulations of buildings and equipment. The approach taken discretized the cost function and applied a non-smooth optimization algorithm to determine the set of controls that minimize the sum of costs over the specified time.

Genetic Algorithms (GA) are stochastic search algorithms that borrow some concepts from nature. At the start of the algorithm, an initial population is generated, either randomly or according to some rules. The reproduction operator selects population members (set of optimization variables) from the previous population to be parents for new members. This parenthood selection can range from a totally random process to one that is based on the member's fitness value (value of the objective function for each member).

Each new generation is formed by the action of genetic operators on the older population. Finally, the members of the population pool are compared via their fitness value in order to choose the optimal solution. A GA is left to progress through generations, until certain criteria (such as a fixed number of generations, or a time limit) are met [25].

Artificial neural networks are computational models of which the most important features are the abilities to learn, to associate, and to be error-tolerant [58]. Unlike conventional problem-solving algorithms, neural networks can be trained to perform a particular task. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples; the neural network will then extrapolate the mapping between input and output data. The neural network consists of an input layer and an output layer of neurons. The neurons are the processing units within the neural network and are usually arranged in layers. The information is propagated through the neural network layer by layer, always in the same direction. Besides the input and output layer there can be other intermediate layers of neurons, which are usually called hidden layers.

After training, the neural network can be used to recognize data that is similar to any of the examples shown during the training phase. This method can be suitable for outside conditions and internal load prediction [29, 59]; also it is possible to train the neural network with simulation results and use it to increase optimization speed [50].

Fuzzy Logic was initiated in 1965 [60], by Lotfi A. Zadeh, professor for computer science at the University of California in Berkeley. Basically, Fuzzy Logic (FL) is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Fuzzy Logic provides a different way to approach a control or classification problem. This method focuses on what the system should do rather than trying to model how it works. One can concentrate on solving the problem rather than trying to model the system mathematically, if that is even possible. On the other hand the fuzzy approach requires a sufficient expert knowledge for the formulation of the rule base, the combination of the sets and the defuzzification. In general, the employment of fuzzy logic might be helpful, for very complex processes, when there is no simple mathematical model (e.g., inversion problems), for highly nonlinear processes or if the processing of expert knowledge is to be performed [61].

Keeney and Braun [62] developed a building optimization with zone temperature setting as controls and a combination of energy cost and penalized human comfort as the cost. The "complex" method, an extension of the "simplex" method to constrain optimization problems, was used to solve this optimization problem over a 24-hour horizon. Based on detailed optimization, two simplified approaches were proposed for online implementations, where one approach takes two constant zone-sensible pre-cooling rates and the other applies a constant cooling rate for a given amount of time prior to building occupancy. Their simplified strategies achieved significant energy savings compared to conventional control.

The most common method of building optimization is the genetic algorithm, a search technique used in computing to find solutions to optimization problems. This method will be explained in detail later. Magnier and Haghighat [50] described an optimization methodology based on a combination of an artificial neural network and a multi-objective evolutionary algorithm. They first used a simulation-based Artificial Neural Network (ANN) to characterize building behavior, and then combined this ANN with a multi-objective genetic algorithm (NSGA-II) for optimization. Results of the optimizations showed significant reduction in terms of energy consumption as well as improvement in thermal comfort. Finally, by using the multi-objective approach, dozens of potential designs were revealed, with a wide range of trade-offs between thermal comfort and energy consumption.

Palonen et al. [63] developed a genetic algorithm model for simulation-based optimization problems to solve for the optimal design of building parameters. Their optimization method was mostly based on NSGA-II and Omni-optimizer. The developed genetic algorithm was used to solve single-objective and two-objective problems. As a result of that study, a collection of 26 evolutionary strategies was implemented with three different coding schemes.

Parameshwaran et al. [64] experimentally investigated the combined effect of the energy conservation of the variable refrigerant volume (VRV) system and variable air volume (VAV) system, using a genetic fuzzy optimization method that yielded better thermal comfort and indoor air quality (IAQ) requirements without compromising on the energy savings potential. Based on the three strategies of the supply air temperature, the proposed system achieved 54% in summer and 61% in winter energy savings in design conditions. Furthermore, for the strategies considered the proposed system achieved an annual energy conservation potential of 36%.

Congradac and Kulic [65] discuss the importance of CO_2 control to enhance the IAQ and energy savings potential of the HVAC system through the application of the GA. A simulation was developed in order to power savings by using the suggested method of CO_2 concentration control in a standard HVAC system. They concluded that the savings should not be disregarded. Their results showed up to 20% energy savings for the chiller. They applied results from the optimization problem with MATLAB to the EnergyPlus model of the building and simulations gave them expected results in energy and cost savings.

Wang et al. [52] presented a multi-objective optimization model that could assist designers in green building design. Life cycle analysis methodology was employed to evaluate design alternatives for both economic and environmental criteria. This paper presented the use of an optimization program coupled with an energy simulation program, which allows the design space to be explored in the search for an optimal or near-optimal solution(s) for a predefined problem.

Wright and Farmani [66] simultaneously optimized the building's construction, the size of heating, ventilating and air-conditioning systems, and the HVAC system supervisory control strategy in order to account automatically for the thermal coupling between these building elements. The problem formulation was described in terms of the optimization problem variables, the design constraints, and the design objective functions. The optimization problem was solved using a GA search method. The conclusion was that the GA is able to find a feasible solution with an exponential convergence on that solution. The solutions obtained were near-optimal, the lack of final convergence being related to variables having a secondary effect on the energy cost objective function.

The literature review on building optimization methods showed that the most common, tested, and validated method of optimization for integrating with simulation tools is the genetic algorithm.

2.4 Important methods for increasing optimization speed and accuracy

The class of optimization problems solved in this thesis is non-linear that for many conditions a global solution may not be reached. Using different optimization algorithm may result in different solutions with varying computational time. In this thesis for different optimization algorithms whenever calculation of an algorithm takes less time to reach similar energy savings of another algorithm it is called faster optimization and whenever by spending similar calculation time the results show higher energy savings it is called increasing optimization accuracy.

Researchers develop new optimization algorithms continuously to improve speed and accuracy of solutions to local and global optimization problems. However, none of these algorithms can be introduced as the best optimization algorithm. Each algorithm can be more suitable in a different problems compared to the other algorithms. Hybrid optimizations are introduced to implement two or more algorithms for the same optimization problem. A hybrid optimization uses advantages of each algorithm to compensate for disadvantages of the others [67].

All stochastic methods are very time-consuming because of the large number of calculation of the objective function that is necessary for optimization. The idea of coupling them with a more efficient local search, leading to one type of hybrid optimization, this method has shown its efficiency in many problems in the last decade [68–71]. Evolutionary algorithms as strong global optimization techniques are very useful to apply in large-scale problems that have many local optima. However, these optimization algorithms are very time-consuming, and their convergence performance is very poor. On the other hand, local search algorithms have very fast convergence but they can easily be trapped in local optimum. The incorporation of global and local search methods could eliminate their difficulties and disadvantages while offering the advantage of both optimization methods. Combining a local search with a GA as a global optimization method can be done in different ways [72].

A combination of GAs with the conventional optimization techniques is recommended to improve the convergence and the search efficiency [73, 74]. GAs are powerful at global searching with very slow convergence, while the local optimization techniques can converge very fast with lack of a global search opportunity; so the hybrid of these algorithms can benefit the global search potential of GAs with conventional optimization techniques, local search accuracy and speed, and compensate for their individual deficiency, thus outperforming either one them [75].

Mousa and Kotb [76] proposed a hybrid multi-objective approach for computing fuel cost and emission. They implemented their approach to iteratively update a finite-sized archive of non-dominated solutions. Also, a local search method was introduced as a neighborhood search engine. The proposed technique has been effectively applied to solve a problem considering two objectives simultaneously, with no limitation in handing more than two objectives.

Genetic algorithm method is combined with fuzzy logic systems to improve their performance, for example, to provide an appropriate set of fuzzy rules for classification problems [77] and to improve the fuzzy logic controller [78]. Konga et al. [79] proposed a case-based reasoning (CBR) hybrid strategy to enhance multi-objective evolutionary algorithms. Their experimental results show low accuracy and divergence potential in handling the multi-objective optimization problems for pure evolutionary algorithms, and that the hybrid strategy based on CBR can improve optimization results by reusing historical cases in dynamic environments.

Ishibuchi et al. [77] proposed a GA-based method for choosing an appropriate set of fuzzy if-then rules. They introduced a method to find a minimum set of fuzzy if-then rules that can correctly classify all training patterns. A combination of optimization problems with two objectives are formulated and solved in their research. These objectives include maximizing the number of correctly classified patterns and minimizing the number of fuzzy if-then rules. The self-tuning fuzzy logic design was investigated by many researchers for various problems [82–83]. Rahil et al. [84] proposed an approach for learning uncertain linguistic rules from training data and improved it for uncertain rule-based pattern classification systems. The main advantages of the proposed rule extraction method are higher interpretability of the rule set and more robust and reliable results than the other methods.

Researchers compared GAs and PSOs (particle swarm optimization) and approve that a hybrid of the standard GA and PSO models could lead to further advances [80]. Chia-Feng [81] proposed a new evolutionary algorithm, HGAPSO. He combined the new individual generation function of both GA and PSO. His results show the advantages of HGAPSO over GA and PSO by applying them in temporal sequence production and dynamic plant control problems. One hybrid algorithm is developed based on a combination two global optimization algorithms, genetic algorithm (GA) and particle swarm optimization (PSO), and is thus called HGAPSO. In HGAPSO, individuals in a new generation are created, not only by crossover and mutation operation as in GA, but also by PSO. Since PSO and GA both work with a population of solutions, combining the searching abilities of both methods seems to be a good approach. Parallel and sequential genetic algorithms (P-GAs) are other techniques for searching complex problem spaces for an optimum. Parallel GAs have many interesting unique features that deserve in-depth analysis [85, 86]. These characteristics include [87]:

(1) The reduction of the time to locate a solution (faster algorithms),

(2) The reduction of the number of function evaluations (cost of the search),

(3) The possibility of having larger populations with the parallel platforms used for running the algorithms, and

(4) The improved quality of the solutions worked out.

The common problems faced by researchers and developers in using neural network techniques are optimization of input selection, network design and learning conditions. Various problems of neural network design can be optimized using GAs. Examples include selecting relevant input variables, determining the optimal number of hidden layers, nodes and connectivity, and tuning the learning parameters [88]. Another approach of combining neural networks and GAs is genetic training. GAs have been used to search the weight space of a neural network without the use of any gradient information.

The good approximation performance of the neural network (NN) and the effective and robust evolutionary searching ability of the genetic algorithm are very useful in a hybrid sense, where NNs are employed in predicting the objective value, and GA is adopted in searching optimal designs based on the predicted fitness values. Forms of objective functions of many practical problems are often not explicitly known in terms of design variables, or sometimes it is not easy to obtain the objective value efficiently. So, it needs complicated analysis or time-consuming simulation to evaluate the performance of design variables. If the GA is applied to such problems, much computational time will be spent in fitness evaluation while less time will be paid for space search, so that the efficiency and quality of the algorithm would be degraded. Recently techniques such as regression and neural network have been pursued to approximate the usually unknown input-output function implied by the underlying simulation.

Wang [89] proposed a hybrid GA–NN strategy for optimization problems without an explicitly known form of objective functions, and the feasibility and effectiveness of the framework are demonstrated by successfully applying it to a pressure vessel design problem.

2.5 Building load and occupancy prediction for multi-hour optimization

A fundamental goal of energy-efficient and high-performance buildings is to create a comfortable, healthy and productive environment for the occupants while maintaining minimum energy consumption. Information regarding the number of occupants in a building space is an important component to achieving this task and is useful for numerous applications, such as lighting control or demand-controlled ventilation. Occupant presence and behavior in buildings has been shown to have large impacts on space heating, cooling and ventilation demand, energy consumption of lighting, and building controls [89]. The energy performance in buildings is influenced by many factors, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and HVAC systems, occupancy and their behavior. This complex situation makes it very difficult to accurately implement the prediction of building energy consumption. In this case prediction of effective parameters separately and simulating the building energy consumption base on predicted parameters seems the best solution for this problem.

Reinhart et al. [90] determined occupant presence for lighting software by using a simplified stochastic model of arrival and departure. Bourgeois et al. [91] integrated an occupancy model based on Reinhart's algorithm into ESP-r to investigate lighting use. However, most of the previous occupancy presence models were either tested on a single-person office or presented a specific application such as lighting control. Page et al. [92] have targeted individual occupancy behaviors by developing a generalized stochastic model for the simulation of occupant presence with derived probability distributions based on Markov chains. However, some of the occupant behavior derived from the stochastic model was based on the assumption that occupants will interact with different appliances in the space, and the validation was conducted in single-person occupied offices.

Yamada et al. [93] 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. The predictions were later used to estimate building performance in order to achieve energy savings and indoor comfort.

Westphal and Lamberts [94] predicted non-residential buildings' annual heating and cooling load simply based on some weather variables, including monthly average of maximum and minimum temperatures, atmospheric pressure, cloud cover and relative humidity. Their results showed good accuracy on low mass envelope buildings, compared to detailed simulation tools such as ESP, BLAST, and DOE-2.

Lei and Hu [95] evaluated regression models for predicting energy savings from retrofit projects of office buildings in a hot summer and cold winter region. They showed that a single variable linear model is sufficient and practical to model the energy use in hot and cold weather conditions.

Olofsson and Andersson [96] developed long-term energy demand (the annual heating demand) predictions based on short-term (typically 2–5 weeks) measured data for single-family buildings by using the neural network method.

Kubota et al. [97] used a genetic algorithm for variable extraction, which means translating original variables into meaningful information that is used as input in the fuzzy inference system.

2.6 Including demand response in integrated control

A variety of demand response methods have been applied to building system management for different components such as HVAC, lighting and daylighting, and miscellaneous equipment. These methods are used to find the best response to input signals of energy price or energy consumption limitation.

Some of these methods for HVAC and lighting are mentioned in Table 2-1. Only a few major demand response studies that relate to building energy efficiency and integrated control are discussed here.

Table 2-1: Demand response strategies for HVAC and lighting [98]

System	Strategy
HVAC	
Global Zone control with EMCS Zones (VAV)	Global set-point relaxation
EMCS (DDC) Zones (VAV)	Set point relaxation at zones Reduce fan speed or volume Reduce duct pressure set point
Any equipment with EMCS	Depending on equipment
Roof Top Units without EMCS	Quantity reduction
Constant Volume, Pneumatic	Reduce cooling
Lighting	
Zoned lighting with dimmable ballasts and central control	Dimming
Zoned lighting with small zones and central control	Switching perimeter zones or bi-level switching
Zoned lighting with local control	Panel based switching
Local switches in workplaces	Panel based switching

Kiliccote and Piette [45] discussed recent research results and new opportunities for advanced building control systems to provide demand response (DR) to improve electricity markets and reduce electric grid problems. The main focus of this paper was the role of new and existing control systems for HVAC and lighting in commercial buildings. A demand-side management framework from the building operations perspective with three main feature, daily energy efficiency, daily peak load management, and event-driven and dynamic demand response, was presented. The paper also described results from three years of research in California to automate DR in buildings. In another paper [46] they presented a preliminary framework to describe how advanced controls can support multiple modes of operations including both energy efficiency and demand response (DR). In this paper they provided an overview of the economic opportunities for demand-responsive control technologies and strategies in commercial buildings.

Carmen et al. [47] presented three case studies on commercial buildings that were using advanced monitoring and control technologies to implement integrated energy efficiency (EE) and demand response (DR) strategies. This research established that integrating EE and DR can generate substantial value by increasing the demand-side resource potential while reducing overall administrative and implementation costs.

Charles et al. [99] reviewed the relationship between energy efficiency and demand response and discussed approaches and barriers to coordinating energy efficiency and demand response. The paper was intended to support the 10 implementation goals of the National Action Plan for Energy Efficiency's Vision to achieve all cost-effective energy efficiency by 2025. Objectives of this paper were 1) summarizing existing research on the relationship between energy efficiency and demand response; 2) presenting new information, gathered through interviews with program administrators, customers, and service providers, on the coordination of energy efficiency and demand response, focusing in particular on current practices and opportunities; 3) discussing barriers to coordinating energy efficiency and demand response programs.

2.7 Summary of literature review

The main literature related to integrated building optimization and important methods and strategies are reviewed and discussed. Based on the literature review, several issues emerge that warrant further research in order to achieve better integrated building control and optimization. These issues include:

- Whole-building integrated control vs. limited number of zones: very few studies investigate integrated control for an entire building.
- All building control parameters versus a subset of parameters: most previous work in integrated building control just focused on integrating some of the possible parameters. Identification of all possible parameters and strategies for integration and development of a corresponding advanced control method still need more investigation. Modification in current simulation tools (e.g., DOE-2) is necessary for investigating all parameters and strategies.
- Multi-hour optimization versus static optimization: most previous work applied their optimization just for the current hour without considering the effect of this optimization

on future-hours. Dynamic optimization requires accurate prediction of building load and outside conditions for future hours.

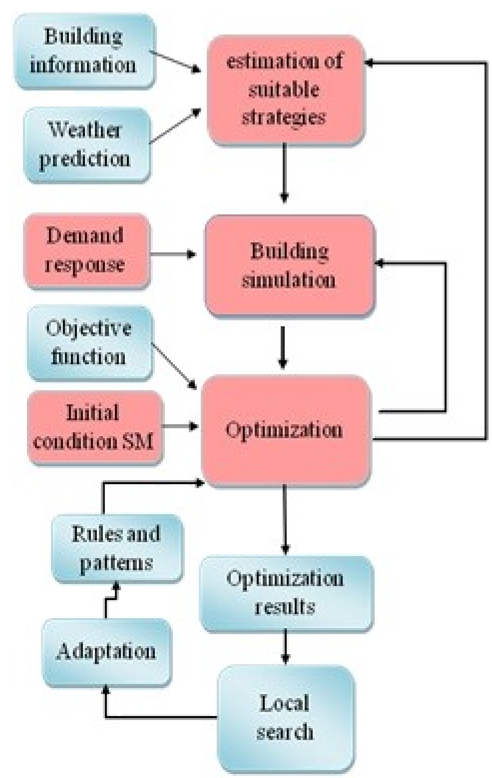
- Introducing a fast and accurate optimization strategy that can be integrated with building energy simulation software that can accept a large number of variables.

3 Methodology

In this research the integrated building energy optimization tool is developed based on connecting the building energy simulation software (DOE-2) and the optimization method in MATLAB (GA). Developed optimization tools can be used for integrated energy optimization of any building types and sizes. It can be used for energy optimization of building with different structures and materials, systems, and schedules. By developing considered building model in DOE-2, integrated energy and cost optimization can be applied to the model without significant effort. In this research application of the developed integrated optimization tool on nighttime ventilation and optimal shade position are investigated for comparison and validation. The developed integrated tool for the whole building energy optimization was applied to a typical office building in Montreal. The results are used to investigate potential of energy savings and evaluating optimization tools.

To reach the main objective of this research—developing an integrated optimization tool that can improve whole-building energy consumption and energy cost while satisfying occupancy comfort—a few necessary steps should be done. These steps include:

- Selecting or developing an appropriate building energy consumption and cost calculation model
- Choosing a suitable optimization and decision-making method
- Integrating the building model and optimization method for whole-building optimization
- Developing strategies and techniques to increase speed and accuracy of optimization



To obtain necessary knowledge for satisfying these required steps, simplified and small problems are defined and solved. These problems include:

- Night-time ventilation strategy investigation
    - Adding function to DOE-2
    - Using genetic algorithm
    - Training neural network

- Shade position effect and optimization
- Optimization methods comparison (GA, SA, PS, Fuzzy) and their integration
- Building integrated optimization development
    - Using RC-network model and nonlinear optimization
    - Developing integrated optimization tool

Methodologies used for each of these steps and problems are discussed in detail in this chapter.

3.1 Governing equation for building energy calculation

For each zone in a building, it is possible to apply energy, mass and momentum balances, depending on the type of required analysis. In addition, the zones of the building are subject to many energy exchange processes, such as heat and vapour gains from occupants, solar energy transmitted through glazing, infiltration, and air exchange with other spaces. Finally, the heat gain to the building interior from lights and other electrical appliances serves as a coupling between this control volume and the electrical instruments. At the basic level, a single control volume represented by a single node can be used to describe the volume of fluid inside the zone. This volume is bounded by solid constructions and is subject to heat transfer by convection, fluid exchange with its neighboring volumes, infiltration from the exterior, heat and vapour gains from occupants, plant interaction, and so on.

The fundamental equation governing these exchanges is an energy balance of the form

$$\rho_i V_i c_i \frac{\partial T_i}{\partial t} = \sum_{j=1}^{n} q_{ij} + q_{in} \tag{3-1}$$

V_i is the volume (m^3) of the fluid volume i, ρ_i is its average density (kg/m^3), c_i is its average specific heat (J/kgK) and T_i is its average temperature (°C). The left-hand side of the equation represents the thermal capacitance of the fluid volume. In the right-hand side of the equation the $\sum_{j=1}^{n} q_{ij}$ term is the sum of the energy rate (W) that interacts with the control volume (surface to fluid heat transfer and fluid flow from other fluid volumes) and the q_{in} term is the energy generation inside control volume.

The general form of the equation describing the convective heat transfer rate (W) between a surface s and the fluid volume i is

$$q_{is} = h_{cs} A_s (T_s - T_i) \tag{3-2}$$

T_s is the surface temperature, A_s is the contact area (m^2) with the fluid volume and h_{cs} is the heat transfer coefficient (W/m^{2}K).

The form of the equation describing the rate of energy exchange (W) due to fluid flow between two fluid volumes i and j is

$$q_{ij} = \dot{m}_{ij} c_j (T_j - T_i) \tag{3-3}$$

$\dot{m}_{ij}$ is the pressure/temperature driven mass flow rate (kg/s) between the two volumes, c_j is the specific heat of the fluid transferred from the neighboring volume and T_j is its temperature.

Applying the previously defined equations to the building zone with convection to interior and exterior walls, also infiltration and ventilation and internal heat gain gives the following expression

$$\rho_i V_i c_i \frac{\partial T_i}{\partial t} = \sum_{j=1}^{n} h_{cij} A_{sj} (T_{sj} - T_i) + \sum_{k=1}^{m} \dot{m}_{ik} c_k (T_k - T_i) + q_i \tag{3-4}$$

Appling forward time step to the partial derivative term, over some finite time interval lead to:

$$\frac{\partial T_i}{\partial t} = \frac{T_i^{t+\Delta t} - T_i^t}{\Delta t} \tag{3-5}$$

The net rate of heat flow, q_{rad}, radiated by a body at temperature T_2 surrounded by an environment at temperature T_1 is given by the Stefan-Boltzmann Law [100]

$$q_{rad} = \sigma A \varepsilon (T_2^4 - T_1^4) \tag{3-6}$$

Where σ is the Stefan-Boltzmann constant, A is the surface area of the radiating object and ε is the total emissivity of its surface having absolute temperature of T_2.

If the temperature difference $\Delta T = T_2 - T_1$ is small, then it is possible to expand radiation heat flow equation as Taylor series around T_1 and obtaining a linear relationship:

$$q_{rad} = 4\sigma A \varepsilon T_1^3 (T_2 - T_1) = h_{rad} A \,\Delta T \tag{3-7}$$

in this equation $h_{rad} = 4\sigma A \varepsilon T_1^3$ can be considered as a radiation heat transfer coefficient.

These are the basic equations that can be used for the calculation of a fluid volume's temperature. Using these equations for calculating energy consumption for an entire building with several zones and parameters is very complicated. As a result, to have an accurate and fast energy calculation for all kinds of buildings and systems, it is necessary to use building simulation tools. Integrating optimization and simulation tools requires an optimization method that can work without knowing the exact equation for calculation of energy consumption. One widely used and validated method of this kind of optimization is the genetic algorithm.

3.2 Genetic algorithm

Genetic Algorithms (GA) are stochastic and random search algorithms that borrow their ideas from nature [101]. GA maintains a population pool of candidate solutions called variable-sets. Each variable-set is a collection of optimization variables values. Associated with each variable-set there is a fitness value which is determined by a user defined function or program, called the objective function. The objective function calculates the value proportional to the candidate solution's suitably and/or optimality. Figure 3-1 shows the control and data flow of GA [102]. At the start of the algorithm, an initial population of variable-sets is generated. Initial members of the population may be randomly generated, or generated according to some rules. In this research random population generation is chosen for creating initial population. The reproduction operator selects variable-sets from the population to be parents for a new variable-set and enters them into the population pool. Selection of a variable-set for parenthood can range from a totally random process to one that is based by the variable-set's fitness. Stochastic uniform method was chosen for selection method. This method creates a line in which the line is divided to sections proportional to parents' scaled value. The algorithm moves along the line in steps of equal size. At each step, the algorithm selects a parent from the section it lays on. The first step is a uniform random number less than the step size.

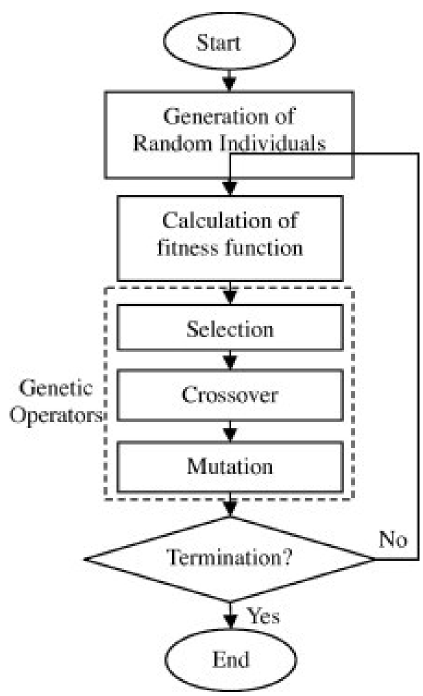


Figure 3-1: Control and data flow of Genetic algorithm optimization method [102]

The cross-over operator decides changing process of two variable-sets. Two parent variable-sets are selected from the population pool then based on the cross-over rate, which is a real number between zero and one, a new variable-set from the parents are produced with determined probability. If the cross-over was performed, a child variable-set is created. The cross-over operator decides what characteristic of parents is passed onto the child variable-set; in other word, it defines the equation of calculating the new variable-set from parents' variable-sets. The new variable-set is entered into the population pool and it may represent an unexplored point in the search space.

The mutation operator takes each variable-set in the population pool and randomly changes it. The probability of mutation occurring on any variable-set is determined by the user specified mutation rate. Variable-sets mutated or otherwise, are put back into the population pool after the mutation process. Thus each new generation of variable-sets are formed by the action of genetic operators (reproduction, cross-over and mutation) on the older population. The variable-sets are compared based on their fitness value to derive a new population, where the variable-sets with worse fitness value may be eliminated. The exploring for assessing the survival of each variable-set into the next generation is called the replacement strategy.

The process of reproduction, cross-over, mutation and formation of a new population completes one generation cycle. A GA is left to progress through generations, until certain criteria (such as a fixed number of generations, or a time limit) are met. Table 3-1 shows options and values that are chosen for genetic algorithm optimization in this research.

Table 3-1: Options and values that are used in genetic algorithm in MATLAB

Option	**Set**
Population type	Double vector
Population size	Depends on number of variables
Creation function	Uniform
Scaling function	Rank
Selection function	Stochastic uniform
Elite count	0.05 * Population size
Crossover fraction	0.8
Mutation function	Adaptive Feasible
Stopping Criteria	Generations (depends on number of variables)

3.3 Neural network

Artificial neural networks are computational models that are used for estimation or approximation of functions that are generally unknown and they can depend on a large number of inputs. The most important feature of a neural network is its abilities to learn that means it can be trained to do a specific job. This is done by describing the problem with presenting set of examples, namely pairs of input and output samples; the neural network will then learn the approximate relation between inputs and outputs to estimate the output based on new input. The neural network at least consists of an input layer and an output layer. Each layer includes neurons that are the processing units within the neural network. The calculation is propagated through the neural network from input layer to output layer [103]. In addition to input and output layer there can be layers of neurons between them, which are usually called hidden layers (Figure 3-2). Finding relations and equations that connect neurons of each layer to the next layer require training process. After training, the neural network can be used to recognize data that is similar to any of the examples shown during the training phase. This method can be suitable for outside condition and internal load prediction, also it is possible to train neural network with simulation results and use it for optimization to increase optimization speed.

The trained network for building energy and cost prediction problems in this research is a feed forward network with the tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. The trained network inputs are control variables and it has one hidden layer that number of neurons in this hidden layer depends on number of control variables. The number of neurons in hidden layer changed from 15 to 25 neurons based on number of control variables and it is chosen by comparing mean square error of sample data and predicted results from NN for different number of neurons.

According to McKay [104], a sample of about two times of control variables should be sufficient to accurately sample the search space. For building energy and cost prediction, this number of sampling data underestimated the number of cases required for NN training, estimated sampling data that are required for training approximately equals to 30 times of the number of control variables.

During training process sampling data are divided in three groups, 70% of them are used for training, 15% are used to validate that the network is generalizing and to stop training before overfitting, and The last 15% are used as a completely independent test of network validation.

Levenberg-Marquardt is selected as training algorithm for this research. Other available methods are Bayesian Regularization that can be used for some noisy and small problems, and Scaled Conjugate Gradient that uses gradient calculations compare to Jacobian calculations that the other two algorithms use.

If the magnitude of the gradient of performance and the number of validation checks reach to certain amount the training convergence was considered to be acceptable. When the training reaches a minimum of the performance the gradient will become very small. If the magnitude of the gradient is less than 1e-10, the training will stop. The number of validation checks shows the number of successive iterations that the validation performance stays the same. If this number reaches 10, the training will stop. The network's performance can be improved by train it again, increase the number of neurons in hidden layer, and increase the training data set. In case of overfitting that the training set performance is acceptable, but the performance on the test set is significantly worse, then the results can be improved by reducing the number of neurons. If training performance is poor, then increasing the number of neurons should be considered [105].

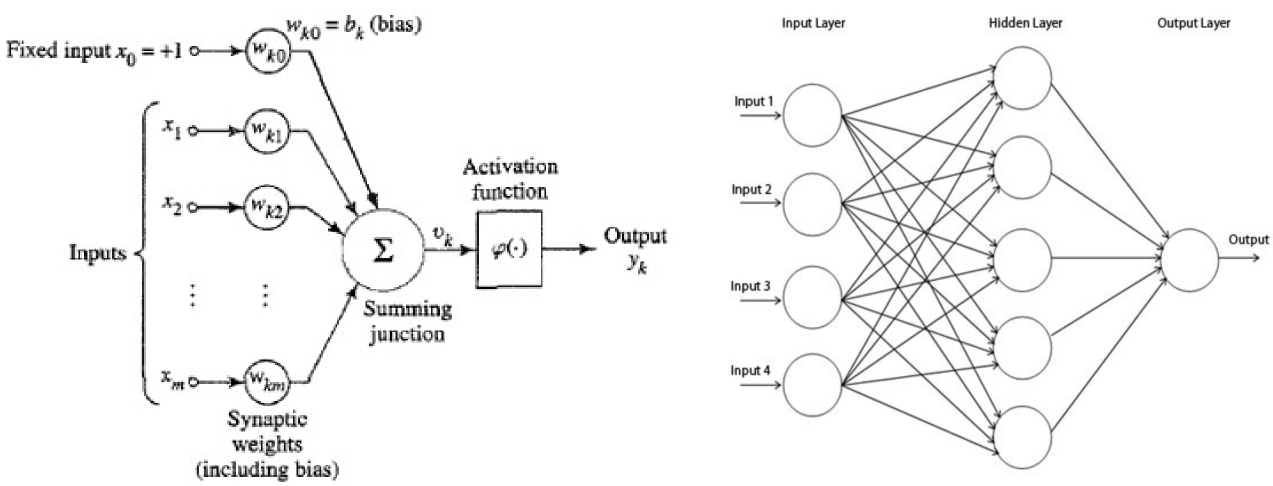


Figure 3-2: Neural Network process and structure [106]

3.4 Integrated optimization with RC-network model and nonlinear programming

The goal of optimization problem is represented by an objective function or cost function. Solving optimization problem is the process of finding the set of design variables, under design constraints, which suit objective function the best. The general optimization problem can be expressed as:

$$\begin{cases} \text{Minimize } f(x) \\ \text{Subject to } x \in X \end{cases}$$

Where x : a decision variable and X: the constraint set

$f(x): X \rightarrow \mathbb{R}$ the cost or objective function

Optimal decision is an $x^* \in X$ such that: $f(x^*) \leq f(x), \forall x \in X$

Constraint can be defined in equality form $\{h_i(x) = 0, i = 1, \ldots, m\}$ or inequality form $\{g_j(x) \leq 0, j = 1, \ldots, m\}$. If $X \subset \mathbb{R}^d$ is continuous, different type of optimization problem can be defined such as:

- Linear programming (LP): f is linear and X is a polyhedron specified by linear equalities and inequalities.
- Quadratic programming (QP): f is convex quadratic and X is a polyhedron specified by linear equalities and inequalities.
- Convex programming: f is a convex function and X is a convex set.
- Nonlinear programming: f is nonlinear, and/or X is specified by nonlinear equalities and inequalities.

Developing building optimization problem require a building model for calculating building energy consumption as an objective function. For investigation of building integrated control effectiveness the RC-network model is chosen for building energy calculation. Developed RC-network model in this research is used to show energy savings potential by applying integrated optimal control, in addition to investigate effectiveness of control parameters in energy savings potential. RC-network model subdivides the thermal system into a number of finite subvolumes called nodes. The thermal properties of each node are considered to be concentrated at the central nodal point of each subvolume. Each node represents two thermal network elements, a temperature (potential) and a thermal mass (capacitance). Resistance are used to represent the heat flow paths through which energy is transferred from one node to another node by conduction, convection, and radiation.

Based on materials discussed in previous chapters, a five zones RC-network model is developed for investigations. In this model resistances are the network elements used to represent the heat flow paths through which energy is transferred from one node to another node. Conduction resistance is computed from the equation: $R = \frac{L}{k\,A}$. Convection resistance is computed from the expression: $R = \frac{1}{h\,A}$ where A is heat transfer surface area, h is convection heat transfer coefficient, k is thermal conductivity and L is the wall thickness.

The overall U-value for the wall can be calculated by: $U = \frac{1}{\sum_{i=1}^{NL} R_i}$ where i is number of layers (NL) in each wall and R_i is conduction resistance of each layer.

The conductive interaction in a multi-zone building can be modeled with simple RC-networks as building blocks. In this formulation, the building is represented by a graph with nodes and edges. A node may represent a physical zone or point inside a wall.

The resulting model of the building consists of a large electrical network of resistors and capacitors of all zones that are connected to each other the RC-network model of one zone is shown in Figure 3-3. For each zone, conduction heat transfer from interior walls, exterior walls with thermal storage and windows with variable conductance (depending on shade position) is considered. Also indoor air heat gains from solar (q_s), artificial light (q_l), occupancies (q_i), ventilated air (q_v), and heating and cooling ($q_{h/c}$) are calculated. Heat transfer from roof and ground are neglected for simplification. RC-network model of entire building and detail information of parameters and schedules are presented in appendix A.

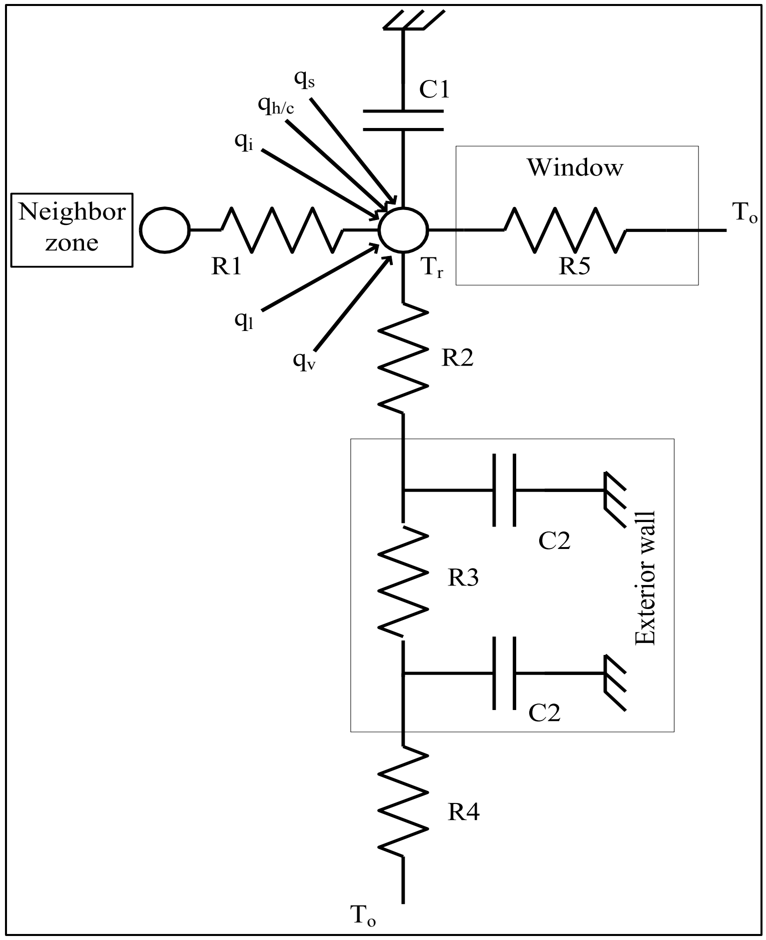


Figure 3-3: RC-network model of one zone. Variables are: C1: air capacitance, C2: Exterior wall capacitance, R1: Interior wall R value, R2: Exterior wall indoor surface convection resistance, R3: Exterior wall R value, R4: Exterior wall outdoor surface convection resistance, R5: variable window conduction, R-value depends on shade position

For calculation of energy or cost function based on RC-network model first it is necessary to calculate total energy consumption of the building:

$$E_{Total} = E_{Chiller} + E_{Boiler} + E_{Fan} + E_{Light} \tag{3-8}$$

Energy consumption of chiller, boiler, and fan is related to the cooling and heating load of zones. Heating and cooling load and related energy consumptions can be defined by the following equations

$$Q_{i,z}(x) = Q_{Cond,Ext}(x) + Q_{Fresh\ Air}(x) + Q_{Cond,Int}(x) + Q_{Light}(x) + Q_{Heat\ gain}(x) + Q_{Solar\ Trans}(x) \tag{3-9}$$

In these equations "z" is zone number, "i" is optimization hour and "x" is vector of control variables. $Q_{Cond,Ext}$ that is conductance heat transfer from the exterior surface can be calculated by following equations

$$Q_{Cond,Ext}(x) = Q_{Cond,window}(x) + Q_{Cond,wall\ ext}(x) \tag{3-10}$$

$$Q_{Cond,window}(x) = \frac{T_I - T_o}{R_5} \text{ Where}$$
$$R_5 = R_{shade,open} + x_{shade}\,(R_{shade,close} - R_{shade,open}) \tag{3-11}$$

$$Q_{Cond,wall\ ext}(x) = \frac{T_I - T_{s,in}}{R_2} \tag{3-12}$$

In these equations T_I is indoor air temperature, T_o is outdoor air temperature, R_5 is windows thermal resistance considering effect of shade position, $T_{s,in}$ is exterior wall inside surface temperature, and R_2 is exterior wall inside surface convection resistance.

$Q_{Fresh\ Air}$ that shows amount of building load caused by outdoor air mass transfer to the building is calculated by:

$$Q_{Fresh\ Air}(x) = Q_{ventilation} + Q_{infiltration} \tag{3-13}$$

$$Q_{ventilation} = \dot{m}_v C_1(T_I - T_0) \text{ and } Q_{infiltration} = \dot{m}_{inf} C_1(T_I - T_0) \tag{3-14}$$

where $\dot{m}_v$ is ventilated air mass flow rate, $\dot{m}_{inf}$ is infiltrated air mass flow rate, and C_1 is air capacitance.

$Q_{Cond,Int}$ is calculated based on zone air temperature T_I, neighbor zone air temperature $T_{I,n}$, and interior wall resistance value.

$$Q_{Cond,Int}(x) = \frac{T_I - T_{I,n}}{R_1} \tag{3-15}$$

Energy consumption of chiller, boiler, and fan are calculated based on heating and cooling energy consumption.

$$E_{Chiller} = \frac{Q_c}{COP}\ ,\ E_{Boiler} = \frac{Q_h}{\eta},\ E_{Fan} = \alpha\, Q_i \tag{3-16}$$

Q_c and Q_h are cooling and heating load. COP and η are performance coefficient of chiller and boiler that are assumed to be constant for simplification of the calculation. Ventilation fan power and energy consumption depends on building required heating and cooling, the value of α that shows the relation between building load and distribution fan energy consumption is assumed equal to 0.25 [107].

In real building heat flows from the human body and lights include both convection and radiation, in developed RC-network model the radiation part ignored for simplification of the model.

For building optimal control two types of objective functions are used:

1. Energy consumption (over several time-interval span)
2. Cost function (over several time-interval span)

Energy objective function is defined as:

$$Energy\ Objective\ Function\ = \sum_{i=1}^{n}\sum_{z=1}^{m} E_{i,z}(x) \tag{3-17}$$

The second summation adds energy consumption of all zones from zone 1 to zone "m" and the first summation considers energy consumption of the current hour (n=1) and future-hours. The cost objective function is defined as:

$$Cost\ Objective\ Function\ = \sum_{i=1}^{n}\left[EP_i \sum_{z=1}^{m} E_{i,z}^{e}(x)\ + GP_i \sum_{z=1}^{m} E_{i,z}^{g}(x)\right] \tag{3-18}$$

where EP_i and GP_i are the electricity and gas price, respectively, at each hour based on time-of-use price.

In this research cost objective function calculation includes time-of-use price associated with hourly energy costs but not demand tariffs that are based on the highest consumption in a billing period.

Table 3-2 shows effective variables and disturbance of the optimization problem. Variables x_1, x_2, x_5, and x_6 are independent control variables and the other variables are dependent variables that were calculated based on independent variables.

Table 3-2: Effective variables and disturbance of optimization problem

Variables	**Disturbances**
x_1= Light ratio x_2= Blind position x_3= Cooling energy x_4= Heating energy x_5= Inside air temp. x_6= Outside air flow rate x_7= Exterior wall inside temp. x_8= Exterior wall outside temp.	V_1= Outside air Temp. V_2= Solar gain V_3= Solar illuminance V_4= Internal heat gain

Format and matrices of developed optimization problem constraints for one zone based on RC-network model are:

$$\begin{cases} linear\ inequality\ constraints: A.x \ \leq b \\ linear\ equality\ constraints: A_{eq}.x = b_{eq} \\ variables\ limits: c \leq x \ \leq d \\ nonlinear\ equality\ constraints: x = M.x + N.v + \sum (P.x + Q.v)\ x_i \end{cases}$$

where the matrices for one zone and current hour optimization can be written as:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ -LP_{max}\ Eff_{lamp} & -Sol_{ill} & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 \\ 1 \\ T_{cs} \\ -Ill_s \end{bmatrix} \tag{3-19}$$

$$A_{eq} = \begin{bmatrix} 0 & 0 & 0 & 0 & -h_i & 0 & \rho_w CP_w L + U_w + h_i & -U_w \\ 0 & 0 & 0 & 0 & 0 & 0 & -U_w & \rho_w CP_w L + U_w + h_o \end{bmatrix}$$

$$B_{eq} = \begin{bmatrix} \rho_w CP_w L\ T_{si-pre} \\ \rho_w CP_w L\ T_{so-pre} + T_o\ h_o \end{bmatrix}$$

$$c = [0 \quad 0 \quad 0 \quad 0 \quad T_{i-min} \quad CFM_{min} \quad T_{si-min} \quad T_{so-min}]$$

The nonlinear constraint can be written as exact equation instead of matrix format in MATLAB

$$\begin{aligned} C_{eq} = &-LP_{max}\ Eff_{lamp} x_1 + \ [(U_{wi-o} - U_{wi-c})T_o + Sol_{heat}]\ x_2 + x_3 - x_4 \\ &+ (U_{wi-o} - U_{wi-c}) x_5\ x_2 + \ [(U_{wi-o} + h_i) + \rho_{air}\ CP_{air}]\ x_5 \\ &- \rho_{air} CP_{air}\ T_o\ x_6 + \ \rho_{air} CP_{air} x_6\ x_5 - h_i\ x_7 \\ &- \left(U_{wi-c}\ T_o + Occ + Equ + \rho_{air} CP_{air} T_{i-pre}\right) \end{aligned} \tag{3-20}$$

Elements of the matrices are calculated based on building parameters and outdoor air conditions such as temperature and solar illuminance and heat gain. These elements show the relation between parameters, constraints and optimization objective function. The objective function is the sum of energy consumptions of lighting, chiller, boiler, and fan that are related to variables x_1, x_2, x_5, and x_6. Objective function is defined as:

$$F(x) = -LP_{max}\ Eff_{lamp}\ x_1 + \left(\frac{1}{COP} + \alpha\right)\ x_3 + \ (\eta + \alpha)\ x_4 + Eff_{Fan}\ x_6 \tag{3-21}$$

Above objective function and constraints matrices are developed for one zone RC-network model optimization of current hour. The objective function and constraints matrices for multi zone and multi hour optimization become very huge and complicated. For example the objective function for multi zone (i=1..n) and multi hour (j=1..n) with zones temperature $T_{i,j}$ become :

$$F|_{i,j} = \Bigg\{ \left[a1_{1,1,}x1_{1,1} + a2_{1,1}x3_{1,1} + a3_{1,1}x4_{1,1} + a4_{1,1}x6_{1,1}\right]_{Zone1}\Big|_{T_{i,1..n}} + \left[a1_{2,1,}x1_{2,1} + a2_{2,1}x3_{2,1} + a3_{2,1}x4_{2,1} + a4_{2,1}x6_{2,1}\right]_{Zone2}\Big|_{T_{i,1..n}} + \cdots \Bigg\}\Bigg|_{T_{i-1,1..n}} + \Bigg\{ \left[a1_{1,2,}x1_{1,2} + a2_{1,2}x3_{1,2} + a3_{1,2}x4_{1,2} + a4_{1,2}x6_{1,2}\right]_{Zone1}\Big|_{T_{i+1,1..n}} + \left[a1_{2,2,}x1_{2,2} + a2_{2,2}x3_{2,2} + a3_{2,2}x4_{2,2} + a4_{2,2}x6_{2,2}\right]_{Zone2}\Big|_{T_{i+1,1..n}} + \cdots \Bigg\}\Bigg|_{T_{i,1..n}} + \cdots \tag{3-22}$$

Feasible domains for this optimization were developed according to the relation between variables and their constraints. Nonlinear constraints are developed based on effect of thermal storage of external walls and also effect of blind position on conductance heat transfer of the window. Limitations of inside air temperature and outside air flow rate are developed based on thermal comfort range and air quality; moreover, limitations of light ratio and blind position are introduced based on visual comfort range.

All calculations are performed on an hourly basis. For multi-hour optimization, control variables of current hour and the considered period of future-hours are optimized together. Since each hour controller variable affects future hours energy consumption because of the thermal storage of the walls and air, it is possible to increase energy savings potential by optimization of all the hours of the considered time period simultaneously.

Outdoor air temperature is used for the current hour and future-hours from the meteorological weather data of Montreal. In addition, solar heat gain and solar illuminance from windows are obtained from the DOE-2 (building energy simulation software) by modeling the same building.

Optimization variables and constraints were defined for the 5-zone (4 perimeters and 1 center zone) office building with 1) heat transfer, solar heat gain, and illuminance from window; 2) heat transfer from internal and external walls; 3) external walls heat storage; 4) internal heat gain from occupants and equipment; 5) ventilation rate; 6) cooling and heating systems load; and 7) illuminance and heat gain from artificial lights. This model was used for integrated optimization of HVAC and artificial lighting systems with the nonlinear optimization method in MATLAB.

3.5 Developing required simulation tool by adding function to DOE-2 (application for nighttime ventilation)

Nighttime Ventilation is a strategy to cool the building with outside air at night to minimize the cooling load during the next hot day. This problem is defined to increase my understanding of building models their advantages and disadvantages. DOE-2.1E is chosen for detailed building energy use and cost analysis. DOE-2 is a widely used, validated and accepted freeware building energy analysis program. It can calculate the energy use and cost for all types of buildings. It has a complete library of building materials and weather data. Most importantly it has available source code and the possibility to add functions to modify the software as it is required for optimization.

The calculation of heat conduction through walls involves solving the one dimensional diffusion equation

$$\frac{\partial^2 T}{\partial x^2} = \frac{1}{\alpha}\frac{\partial T}{\partial t} \tag{3-23}$$

where T is the temperature and α is the thermal diffusivity. In DOE-2 the equation is pre-solved for each wall or roof using triangular temperature pulses as excitation functions. The resulting solutions, called "response factors" are then used in the hourly simulation modulated by the actual indoor and outdoor temperatures [108].

$$q_{inside} = \sum_{i=0}^{\infty} Y_i\, T_{outside}(t - i\Delta) - \sum_{i=0}^{\infty} Z_i\, T_{inside}(t - i\Delta) \tag{3-24}$$

Here, Y_i and Z_i are response factors, q_{inside} is the heat flow at the inside wall surface, and $T_{outside}$ and T_{inside} are temperatures at the outside and inside wall surfaces, and Δ is the time step. This approach assumes that the wall properties, including inside film coefficients, do not change during the simulation. The DOE-2 program in Systems part contains algorithms for simulating performance of the secondary HVAC equipment used to control the temperature and humidity of each zone within the building. DOE-2 does not consider moisture storage effects in the building zone. Instead, it calculates the steady-state moisture balance for each hour and solves for the space humidity that achieves a balance. The moisture content of the air is calculated at three points in the system: the supply air leaving the cooling coil, the return air from the spaces, and the return air after being mixed with outside ventilation air. These values are calculated assuming that a steady state solution of the moisture balance equations each hour will closely approximate the real world. The return air humidity ratio is used as the input to the controller activating a humidifier in the supply airflow or resetting the cooling coil controller to maintain maximum space humidity set points. The moisture condensation on the cooling coils is simulated by solving the coil leaving air temperature and humidity ratio simultaneously with the system moisture balance. Detail information about DOE-2 can be found in the software manuals and references [109, 110].

For further investigation of adding function to DOE-2, the nighttime ventilation strategy was chosen. Methodology included parametric simulations of a typical small office building to estimate the total heating and cooling energy use of the building. Two nighttime ventilation strategies were used: DOE-2 built in schedules and a predictive algorithm to allow nighttime ventilation based on the predicted next day outdoor temperature. The DOE-2 default algorithm requires pre-defined schedules from the operator (that vary by climate region) for duration of nighttime ventilation. The predictive algorithm does not require a pre-defined schedule for nighttime ventilation and it makes decisions for nighttime ventilation schedule throughout the year for all climate regions by itself. The strategies investigated are:

1. Scheduled nighttime ventilation during summer (as defined by the building operator)
2. Nighttime ventilation using a predictive algorithm applied to the entire year
3. Pre-cooling of the building during morning hours and allowing the temperature to gradually increase to the set-point temperature in the afternoon
4. Pre-cooling + nighttime ventilation cooling.

Details of these four strategies are as follows:

Scheduled-driven ventilation during summer, in this strategy, without respect to outside temperature and building cooling or heating mode, a ventilation fan brings in outside air from midnight till the beginning of working hours with a constant air flow rate to cool the building. In our investigations this fixed schedule is set to three months of June, July, and August those have the highest potential of energy savings compared to different months.

Predictive method for nighttime ventilation, in this method a function is added to DOE-21E to change the fan ventilation working hours according to the prediction of the next day outside air temperature that is applied to the entire year. Based on today's minimum and maximum outside temperature and trend of temperature during hours 21 to 24, average, maximum, and minimum outside temperatures for the next day are predicted (Eq 3-25 and 3-26) [111]. The equations are developed through regressions of temperature data and minimizing the error of estimates for predicted temperatures for the summer period. This type of predictive algorithm can be improved through a more thorough analysis of building-related weather data in different climates. This strategy uses predicted temperatures and the cooling characteristics of our building to decide whether to have nighttime ventilation and duration of ventilation (Eq 3-27).

$$TP_{Min} = 0.659\, T_{Min} + 0.307\, T(24) - 0.184[T(20) - T(22)] \tag{3-25}$$

$$TP_{Max} = T_{Max} + 0.349[T(21) - T(21\, PRE)] - 0.1[T(20) - T(22)] \tag{3-26}$$

where

$T(i)$: outside temperature at hour (i)

$T(i\ PRE)$: outside temperature at hour (i) for previous day

T_{Min} and T_{Max}: minimum and maximum outside temperature. TP_{Min} and TP_{Max}: minimum and maximum predicted outside temperature for next day.

$$TP_{Ave} = (TP_{Min} + TP_{Max})/2$$

$$\begin{matrix} Predictive \\ Strategy \end{matrix} \begin{cases} TP_{Ave} < 16\,°C \ \rightarrow No\ Nighttime\ Ventilation \\ 16\,°C < TP_{Ave} < 17.5\,°C \ \rightarrow NV\ from\ 3am\ to\ 8\ am \\ TP_{Ave} > 17.5\,°C \ \rightarrow NV\ from\ 12am\ to\ 8\ am \end{cases} \tag{3-27}$$

Pre-cooling strategy, in this strategy cooling set-points are changed during occupancy hours. For this strategy, the set-point is changed from a lower temperature at the beginning of the day to a higher temperature in the afternoon, when the cooling load is greatest.

Integration of different combinations of two strategies on energy savings, effects of these combinations are investigated by first, combining the strategies 1 and 3, and then combining strategies 2 and 3.

The effects of other parameters such as ventilation rates 0.24 m^3/s to 1.9 m^3/s (500-4000 CFM), temperature difference between inside and outside air 2.7°C to 11°C (5°F - 20 °F), and building thermal mass 488kg/m^2 (100 lb/ft^2) and 976.5 kg/m^2 (200 lb/ft^2) are analyzed with respect to their effects on cooling energy and peak demand.

3.6 Developing required simulation tool by adding function to DOE-2 (prepare for real time optimization)

DOE2 building simulation software was developed mostly for energy calculation of specific building design and comparing effect of building parameters on energy consumption. DOE-2 in its common usage is not designed for real-time building energy optimization. To use it for that purpose requires some modification in accepting input data and in some of the calculation process. The most important limitations of DOE-2 for real-time optimization are:

- Require pre-scheduling of all parameters before simulation
- Do not accept hourly bases input for some parameters even in pre-scheduling
- Could not be run from defined hour with specific conditions in previous hours
- Require modifications in some of the energy calculation process

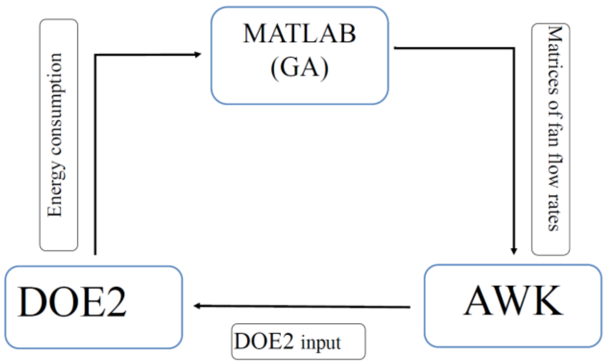
To overcome these limitations first it is necessary to make sure DOE-2 accepts hourly bases input for all control parameters including, indoor temperature, shade position, artificial light power, and outdoor air ventilation rate. DOE-2 does not accept hourly bases input for shade position and outdoor air ventilation rate. To solve this problem functions are added to DOE-2 source code to change these parameters based on inputs in hourly bases instead of a constant number for entire run.

As a next step DOE-2 needs modification to obtain the ability to simulate energy consumption from a specific hour while considering conditions such as indoor temperature of previous hours. In the current calculation process of DOE-2, the simulation can be run from a specific hour; however, the initialization process would be applied to the first hour in the calculation process of DOE-2, and it does not accept indoor conditions of the previous hours as inputs. By adding functions to the source code of DOE-2, the required indoor conditions of the building could be replaced with arbitrary amounts after the initialization process. Having this ability, it would be possible to rerun the simulation hour by hour based on optimization control parameters for the current hour, using necessary previous hours' indoor conditions of the building as an input to this run (calculated in previous hours' runs).

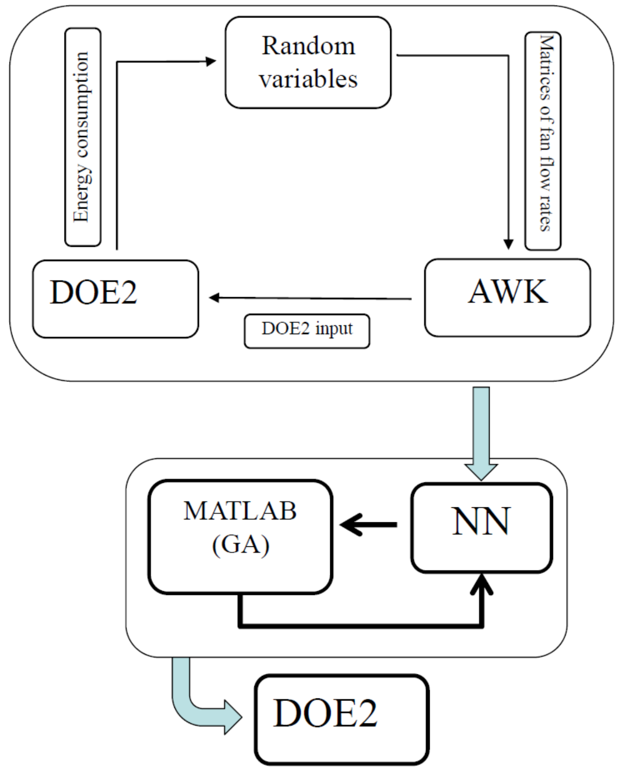
Finally, some of the energy calculation process of DOE-2 required modification by adding functions. For example, the current calculation process of DOE-2 simulates the building with completely open or closed shades, while control optimization requires energy calculation based on exact position of the shade.

3.7 Integrating MATLAB with DOE-2 for detail integrated optimization (Application for nighttime ventilation)

To develop an integrated optimization tool, building energy use and cost analysis software (DOE-2.1E) was used for the building simulation, and a genetic algorithm was used as an optimization method. For integrating MATLAB and DOE-2, first, the genetic algorithm generates variable-sets that are matrices of control parameters values. These matrices include shade position, light power, temperature and outside air flow rate for each zone. In the case of multi-hour optimization, variable-sets include zone-control parameters for the current hour and future-hours. The number of future hours depends on the multi-hour considered time period. After generating a variables-set, MATLAB calls AWK (a text-processing programme) [112] that creates an input file of DOE-2 based on the variable-set. For this step a sample text input file of DOE-2 with marked hourly base control variables is necessary. In this sample input file the values of control variables are replaced with specific and predefined characters that can be identified by AWK software. AWK replaces these characters with the variables-set from MATLAB and creates an input file for DOE-2. Then, DOE-2 is called with MATLAB to run this input file to simulate the building. In the next step, MATLAB calls AWK to search the output file of DOE-2 for desired values of building energy consumption and cost and returns them to MATLAB for that specific variable-set as a fitness value. There are two options available for optimization with integrated DOE-2 and MATLAB, direct and indirect connection between GA and DOE-2. In direct connection MATLAB receives a fitness value for each population during optimization from the DOE-2 calculation. This method is more accurate than indirect connection, since MATLAB optimized energy consumption and cost based on detailed calculated results from DOE-2. However, this process is very time consuming. In indirect optimization, first a neural network (NN) is trained with random generated variables-sets, and then this NN is used instead of DOE-2 for energy and cost calculation during optimization. After optimization with NN, optimized variables are used for energy consumption and cost calculation with DOE-2. Figure 3-4 shows the optimization process.



A



B

Figure 3-4 : Optimization process; A: direct connection of MATLAB and DOE-2; B: indirect connection of MATLAB and DOE-2 by using NN

In a specific case study of nighttime ventilation optimization, nighttime ventilation is optimized by using the above mentioned MATLAB and DOE-2 integrated tool. In this integration the GA method generates a set of flow rates for different hours during the night and sends them to DOE-2. DOE-2 calculates building energy consumption for the entire day based on the specified nighttime fan flow rates and returns the results to GA. This process is continued until GA reaches its maximum iteration and GA introduces the final set of nighttime fan flow rates that reduce building energy consumption. The results of this optimization were used to investigate the effect of influencing parameters such as outdoor temperature, indoor-outdoor temperature difference, and nighttime ventilation duration.

3.8 Integrating MATLAB with DOE-2 for detail integrated optimization (Application for shade position optimization)

Shades positions are optimized by using the same integrated MATLAB and DOE-2 tool that is applied to nighttime ventilation optimization. In this optimization GA generates initial inputs that are matrices of shades positions. Each of these inputs has four elements that are filled in with a number between zero and one (1 = completely closed, 0 = completely open). These numbers show the fraction of each shade position relative to its maximum position. The process of optimization is continued until the GA reaches to its maximum iteration and introduces the final set of shades positions that decreases building energy consumption. The results of this optimization were used to investigate the effect of influencing parameters such as space illuminance set-point, artificial lighting energy consumption and shading conduction and transmission coefficient on building energy use.

Shading of the windows has three different effects on windows coefficients; these coefficients are: 1) radiation heat transmission, 2) illuminance transmission, and 3) conduction heat transfer. Three different types of shading are studied based on their effects on these coefficients:

1) Thin shade, which reduces radiation, illuminance and conduction coefficients when it is completely closed to 25%, 20% and 65% of completely open shade coefficients, respectively;
2) Normal shade, which reduces radiation, illuminance and conduction coefficients when it is completely closed to 15%, 10% and 55% of completely open shade coefficients, respectively; and
3) Thick shade, which reduces radiation, illuminance and conduction coefficients when it is completely closed to 0%, 0% and 45% of completely open shade coefficients, respectively.

The above mentioned values of coefficients for different types of shading are obtained from solar shading and building energy researches [113–115].

Since shade positions have two separate and very important effects, first on building heating and cooling energy and second on building lighting, we investigated these effects based on different shade positions of a window for one specific zone.

3.9 Increasing speed and accuracy of optimization

The most common methods for increasing speed and accuracy of the main optimization algorithm are combining different optimization methods, incorporating an optimization method with a decision-making method, improving optimization parameters and variables, and replacing simulation software with a statistical approach. In this research applying a method to reach higher energy savings while optimization requires same calculation time called increasing accuracy of optimization. Also, reaching similar energy savings in less calculation time called increasing speed of optimization.

3.9.1 Neural network training (application for predicting nighttime fan flow rates)

The application of Neural Networks (NN) is explored to predict the fan flow rate for nighttime ventilation. Diurnal average temperature, temperature range, and hourly outside and inside temperature, in addition to nighttime average temperature, are chosen as possible input data for predicting fan flow rate fractions during the night. Multi-Layer Perceptron (MLP) is used for modelling and neural network is trained and tested using obtained optimized data. The chosen optimized data is divided into three randomly selected groups: the training group, corresponding to 70% of the data; the validation group, corresponding to 15% of data; and the testing group, corresponding to 15% of data. Mean Squared Error (MSE) is used to measure the neural network accuracy. The three-layer network with sigmoid transfer function for the hidden layer and linear transfer function for the output layer is chosen; it can represent any functional relationship between inputs and outputs if the sigmoid layer has enough neurons [116]. Consequently, this three-layer NN is applied with back propagation training algorithms. Finding appropriate architecture needs a trial-and-error method. Input parameters and numbers of neurons in the hidden layer are two effective categories that need to be investigated. Three different types of inputs were investigated: 1) hourly inputs, which include hourly outdoor temperature and hourly indoor temperature; 2) daily inputs, which include diurnal average and range temperature and nighttime average temperature; 3) combination of daily and hourly inputs. The fan flow rate fraction is a number between 0 and 1; as a result, the combination of daily and hourly inputs with MSE less than 0.035 are suitable inputs for the neural network

3.9.2 Stochastic search coupling with local search

The proposed approach integrates the merits of both stochastic method (SM) and local search (LS). To improve the solution quality, the global search technique is applied to whole optimization domain to search for optimal answer area and the local search technique is applied as a neighborhood search engine, where it intends to explore the area near optimal answer to find final result. For coupling global and local search we need to know the appropriate time to shift from the global search to the local search and come back to the global search if it is necessary; also, it is important to find suitable elements and variables for applying the local search. The shift from a global search to a local search is useful when the exploration ability of the global search is no longer efficient. A local search can be called when convergence ratio or difference between mean fitness values of two consecutive generations of the global search reaches an acceptable value. The local search is aimed at making the cost function locally decrease more efficiently than the normal random mutation. For comparison and understanding of the effectiveness and requirements of this coupling method, the pattern search method, as a recommended local search method, and a genetic algorithm, as a stochastic optimization method, are applied to the building RC-network model. The results of applying each of these methods and their integration are compared based on accuracy and time consumption.

3.9.3 Rule-base decision making coupled with stochastic optimization

Stochastic optimization methods have been increasingly applied in conjunction with other techniques such as neural networks, rule-based systems and fuzzy theory. Fuzzy logic and rule base systems have an advantage of using expert knowledge and historical results to generate rules and controlling based on them. However, fuzzy systems become difficult to design for large systems and complicated problems. As a first method for integrating these techniques the genetic algorithm offers an advantage for optimizing the membership function and developing rules for a fuzzy logic system. A hybrid strategy of a stochastic method and a rule-based system also can be developed by using rule-base system to learn the case solutions to guide and promote the search of the evolutionary algorithm, and the best solutions found by the evolutionary algorithm can be used to update the case library to improve the accuracy of case-based reasoning for the following process.

For investigation of these methods first a rule-based system is developed based on results of optimization with a genetic algorithm. Then, rule-base and genetic algorithm are used separately for optimization of building parameters and optimization results are compared. Using rule-base algorithm for better savings required modified and more complex rules based on GA optimization results. Finally, the fuzzy system is coupled with the GA, combining rule-base with a genetic algorithm increases speed of optimization by reducing optimization variables and domain or by using rule-base results as initial population for the GA.

4 Results and discussion of building energy optimization with the RC-network model

Based on a simplified RC-network modeling methodology, the 5-zone (4 perimeters and 1 center zone) office building was modelled with 1) heat transfer, solar heat gain, and illuminance from window; 2) heat transfer from internal and external walls; 3) external walls heat storage; 4) internal heat gain from occupants and equipment; 5) ventilation rate; 6) cooling and heating systems load; and 7) illuminance and heat gain from artificial lights. This model was used for integrated optimization of HVAC and artificial lighting systems with nonlinear optimization method in MATLAB (using “fmincon” routine).

4.1 Building model

The selected prototype building is a one-story office building with 5 zones and a plenum. The building has four perimeter space and one core space that are divided from each other by interior walls. Each space considered as one zone for building thermal model. Each zone has one window with wall to window ratio of 0.5 (Figure 4-1). The total floor area is 464.5 m^2 (5000 ft^2) with a height of 2.4 m (8 ft). There is no shade from other nearby facilities. The building is built with medium weight construction. Interior loads are surface mounted fluorescent lighting at 16 W/m^2, equipment at 10.8 W/m^2, and peak occupancy of 9.3 m^2 (100 ft^2) per person. Infiltration is 0.25 air changes per hour (ACH). Design temperatures for cooling and heating are set at 25.5°C (78 °F), and 21°C (70 °F), respectively. A single variable air volume system serves the entire building.

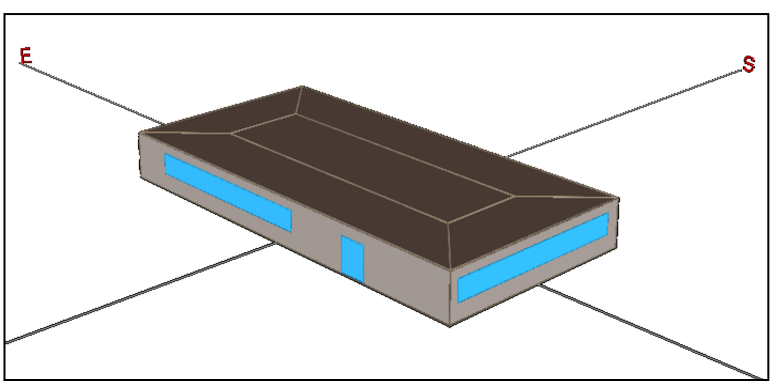


Figure 4-1: Sample building model

The system has a variable speed fan motor, and VAV boxes with a minimum stop of 30%. The cooling and heating system operate from 8am to 6pm weekdays and is off during nights and weekends. The HVAC plant works with gas fired hot water generator and reciprocating air-cooled chiller. Details of building construction and systems are shown in Table 4-1. Building model was developed in DOE-2 software and validated based on results from DOE-2 sample run book [117]. The most similar RC-network model to the described building was developed for optimization in MATLAB that is shown in Figure 3-3. DOE-2 model is used to obtain some of the parameters such as solar heat gain and illuminance from windows that are required in RC-network model.

Table 4-1: Detail of building description

Parameters	**Description**
Floor area [m^2] (ft^2)	464.5 (5000)
Wall construction	Wood shingles, plywood, R-11 fiber insulation, gypsum board
Roof construction	Roof gravel, built-up roofing, R-3 to R-30 mineral board insulation, wood sheathing ceiling
Window glass	0.6 cm plate double pane
Door glass	1.3 cm plate single pane
Interior loads	Lighting=16 W/m^2, equipment = 10.8 W/m^2, people = 9.3 m^2 (100 ft^2) per person
Interior partitions [W/m^2K] (BTU/hr ft^2 F)	U-value = 8.5 (1.5)
Infiltration	0.25 ACH
Chiller	Reciprocating air cooled chiller (COP=3.65)
Boiler	Gas fired hot water boiler (Eff = 85%)

4.2 Optimization variables and constraints

As discussed in chapter 3, Table 3-2 shows effective variables and disturbances of the optimization problem. Variables x_1, x_2, x_5, and x_6 are independent control variables and the other variables are dependent variables that were calculated based on independent variables.

The objective function is the sum of energy consumption of lighting, chiller, boiler, and fan

Objective Function: $\sum_{i=1}^{n}\sum_{z=1}^{m} E_{i,z}(x)$ for one zone (m=1) and current hour optimization (n=1) become $E(x) = \sum ax = a_1\, x_1 + a_2 x_3 + a_3 x_4 + a_4 x_6$

where x_1, x_2, x_5, and x_6 are light ratio, cooling energy, heating energy, and outside air flow rate, respectively. The values of a_i coefficients are calculated based on building and systems characteristics. Details of equations and objectives function calculations are explained in the methodology chapter.

Constraints for this optimization were developed according to the relation between variables and their limitations. Nonlinear constraints were developed based on the effect of thermal storage of external walls and also effect of blind position on conductance heat transfer of the window. Limitations of inside air temperature and outside air flow rate were developed based on thermal comfort range and air quality; moreover, limitations of light ratio and blind position were developed based on visual comfort range.

All calculations are performed on an hourly basis. For multi-hour optimization, control variables of current hour and the considered period of future-hours were optimized together. Since each hour controller variable affects future hours energy consumption because of the thermal storage of the walls and air, it is possible to increase energy savings potential by optimization of all the hours of the considered time period simultaneously.

Outdoor air temperature is used for the current hour and future-hours from the meteorological weather data of Montreal. In addition, solar heat gain and solar illuminance from windows are obtained from the DOE-2 (building energy simulation software) by modeling the same building.

4.3 RC-network model validation

To validate the model, the RC-network model is compared with the results of energy consumption for similar building, as described in Table 4-1, from eQuest (DOE-2) software. The DOE-2 model simulates the building with daylighting control that can open or close the shade based on heat gain as a control parameter. Building temperature and illuminance set-points are equal in both DOE-2 and RC-network models. Building materials and heat transfer coefficients are made as similar as possible. A constant air film heat transfer coefficient and an adiabatic roof in the RC-network model are the most important differences between these two models. To increase similarity of these models, the roof is modeled in DOE-2 with high insulation. Lighting, heating and cooling energy consumptions from DOE-2 and RC-network models are shown in Figure 4-2. The results show good agreement, with less than 15% difference between these two models.

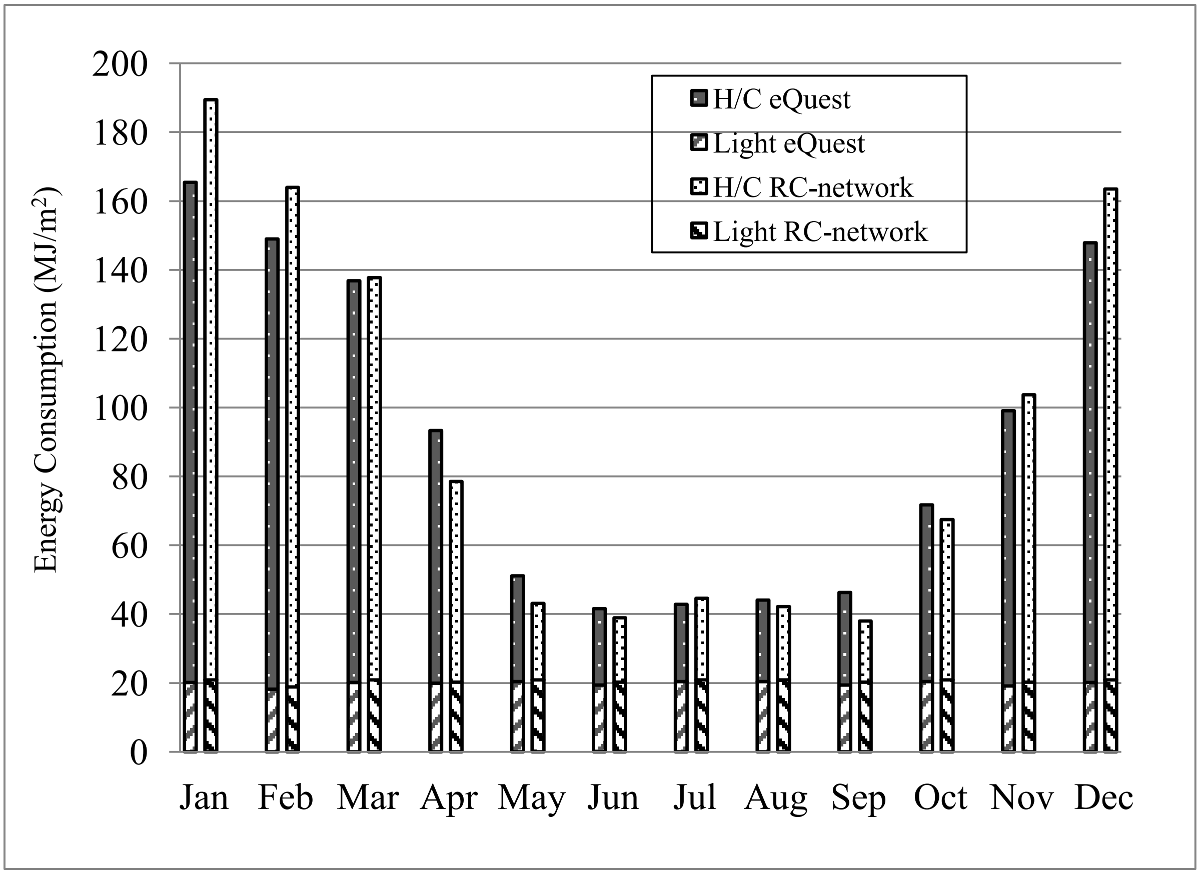


Figure 4-2: Building lighting and heating and cooling energy consumption modeled with eQuest and RC-network. (H/C: heating and cooling energy consumption, Light: lighting energy consumption)

4.4 Integrated optimization and effect of control variables

Scheduled control with constant control parameters is defined for estimating integrated control energy saving potential. Figure 4-3 shows integrated control and scheduled control energy consumption, showing energy savings potential from 20% to 60% by using integrated control compared to scheduled operations. Highest absolute energy savings is about 70 MJ from scheduled control energy consumption of about 140 MJ (50% savings) that occurred during March. Also simulations indicate higher energy savings potentials in transient months (March, April, October and November).

Four control methods were added for investigating the effect of each control parameter separately. We considered and simulated the effect of several control strategies including:

Integrated control: all control variables are optimized based on current hour outdoor conditions and building schedules;

Open shade: window shades are kept open for the entire day while all other parameters are optimized;

Closed shade: window shades are kept closed for the entire day while all other parameters are optimized;

Constant temperature: inside temperature set-point set to 23.8 °C during occupied hours and it can be changed from 18.3 °C to 26.6 °C during unoccupied hours;

Constant fresh air flow rate: fresh air flow rate is kept at minimum for the entire day and all other parameters are optimized; and

Schedule: window shades are always closed, temperature is kept at 23.8 °C during occupied hours, and fresh air flow rate is kept at minimum for the entire day.

Energy consumption related to lighting, and total energy consumption, are shown in Figure 4-4 and Figure 4-5, respectively, for each month for different strategies.

In all strategies artificial lights are optimized to provide required illuminance set-point, while it can go beyond this level to operate as a heat source.

The results showed the fresh air flow rate has less effect on building energy consumption, since using more fresh air increases fan energy consumption. Also, on most days outdoor air temperature is out of range of indoor control set-points. Therefore, using fresh air increases heating or cooling energy consumption. The results also show that the shade position has a very significant effect on energy consumption, since it affects many parameters such as indoor illuminance, solar heat gain and windows conductance. As a result of this important effect of shading, energy consumption of most of the control strategies are approximately the same during the summer since they have same shade position (Figure 4-5). Open shades increased total energy consumption during summer significantly, since solar heat gain has detrimental effects on cooling energy consumption.

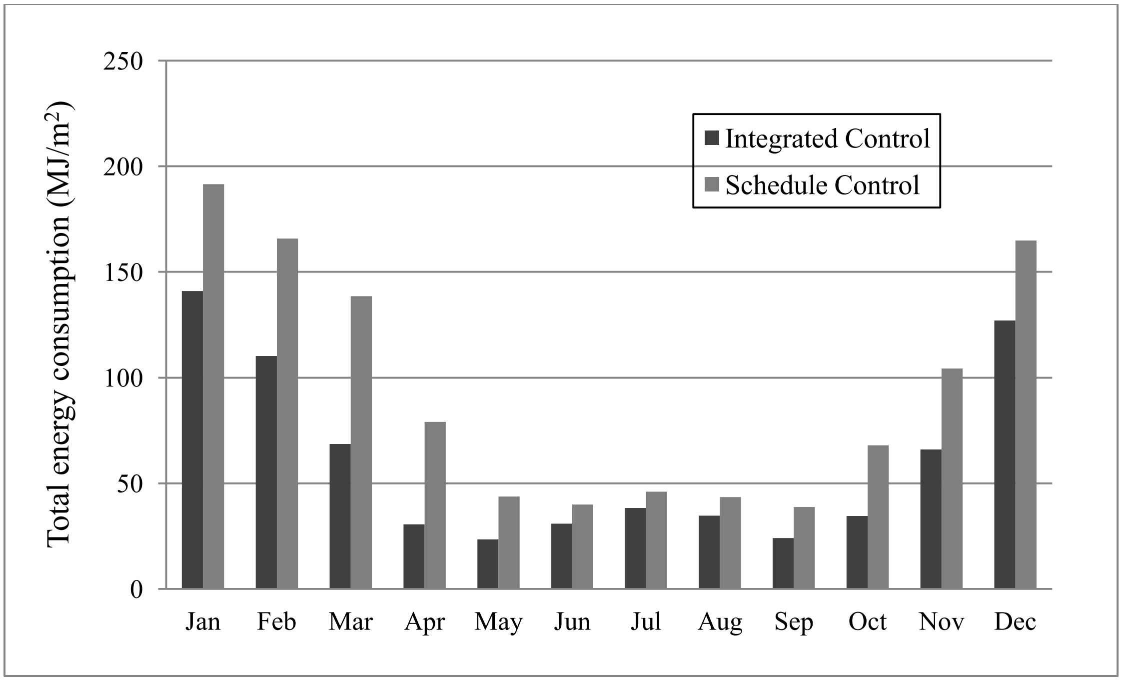


Figure 4-3: Integrated control and schedule control energy consumption

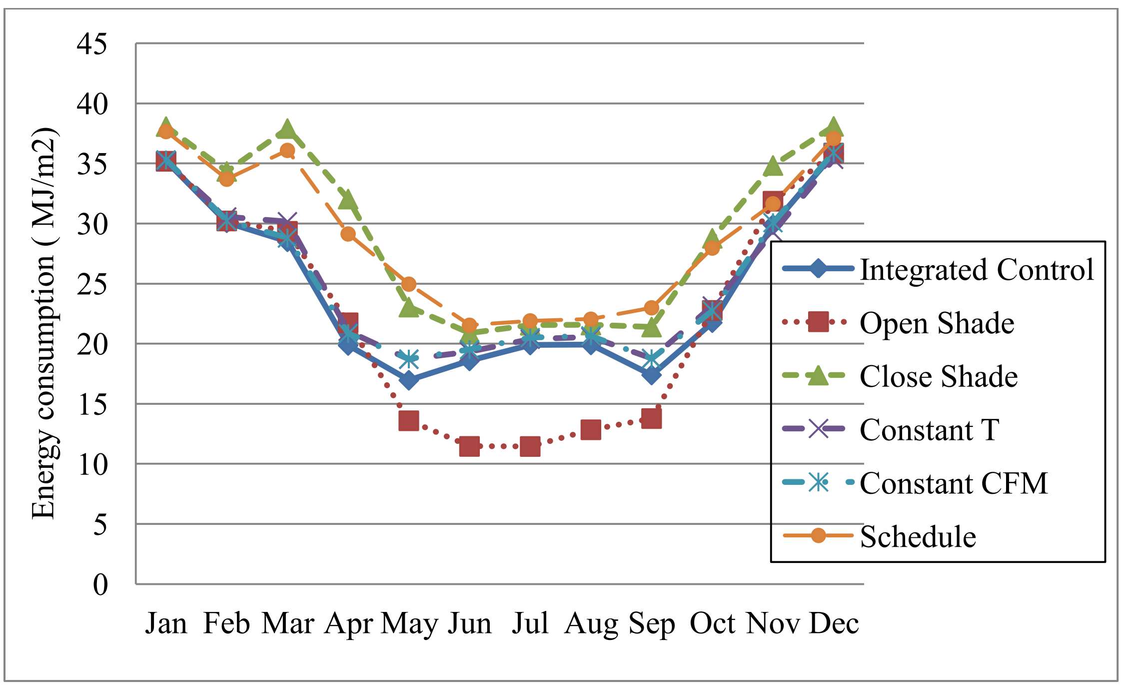


Figure 4-4: Lighting energy consumption for different control methods

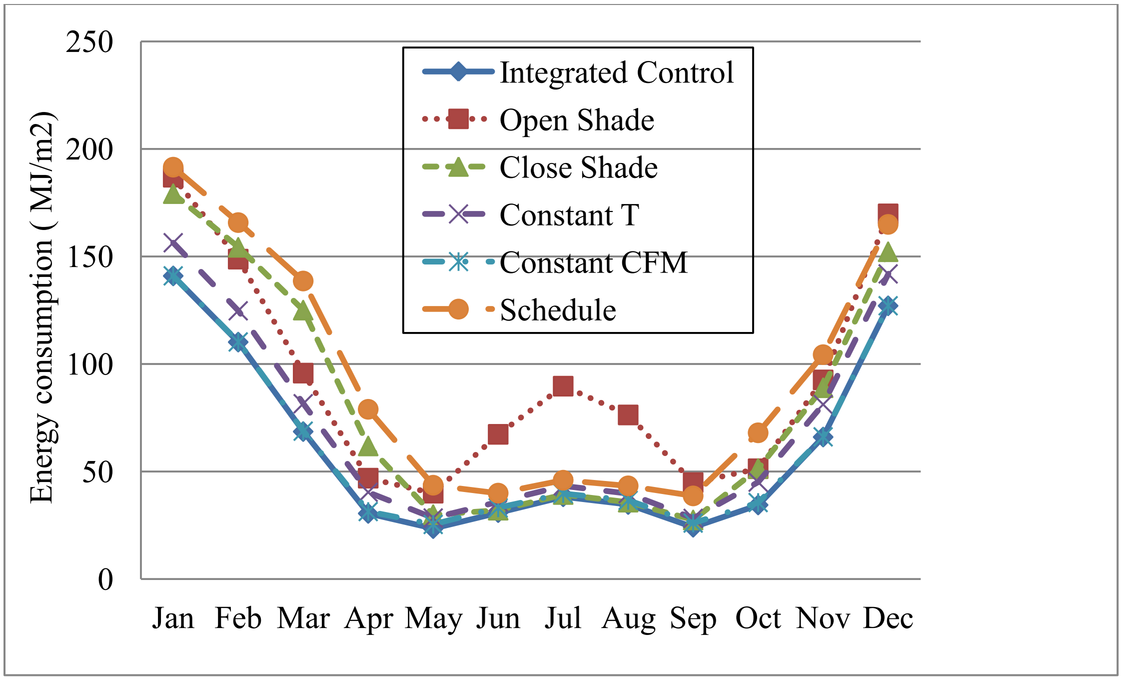


Figure 4-5: Total energy consumption for different control methods

4.5 Effect of integrated control parameters

In addition to the scheduled and integrated control strategies explained before, three new control strategies were further investigated. These semi-integrated strategies are outlined below.

Control of shade based on illuminance: in this control method, shade position is controlled with respect to outdoor illuminance without considering its effect on heating and cooling. The shade is closed during the night and it is open as much as required for indoor illuminance; that is, if outdoor illuminance is less than the indoor set-point, the shade is completely open, and if the outdoor illuminance is more than the indoor set-point, shade position is equal to the ratio of set-point and outdoor illuminance.

Control of shade based on thermal effect: in this case shade position is controlled with respect to heating and cooling without considering its effect on indoor illuminance for control.

Control of individual zones: in this method control variables for each zone are optimized separately. In this case conduction heat gains from neighboring zones are calculated by assuming previous hour temperature as the current hour temperature of these zones. After optimization building energy consumption is recalculated based on applying these separate optimized control variables on each zone of the building and considering their correct heat transfer among each other.

The results from Figure 4-6 and Table 4-2 show that the amount of energy saved by controlling the shade based on heating and cooling is more than the amount of energy saved by controlling the shade based on indoor illuminance. This effect is more important in hot months since shade opening has a detrimental effect on cooling energy. Table 4-2 also shows that by using individual zone control, energy savings will be reduced between 1% and 10%.

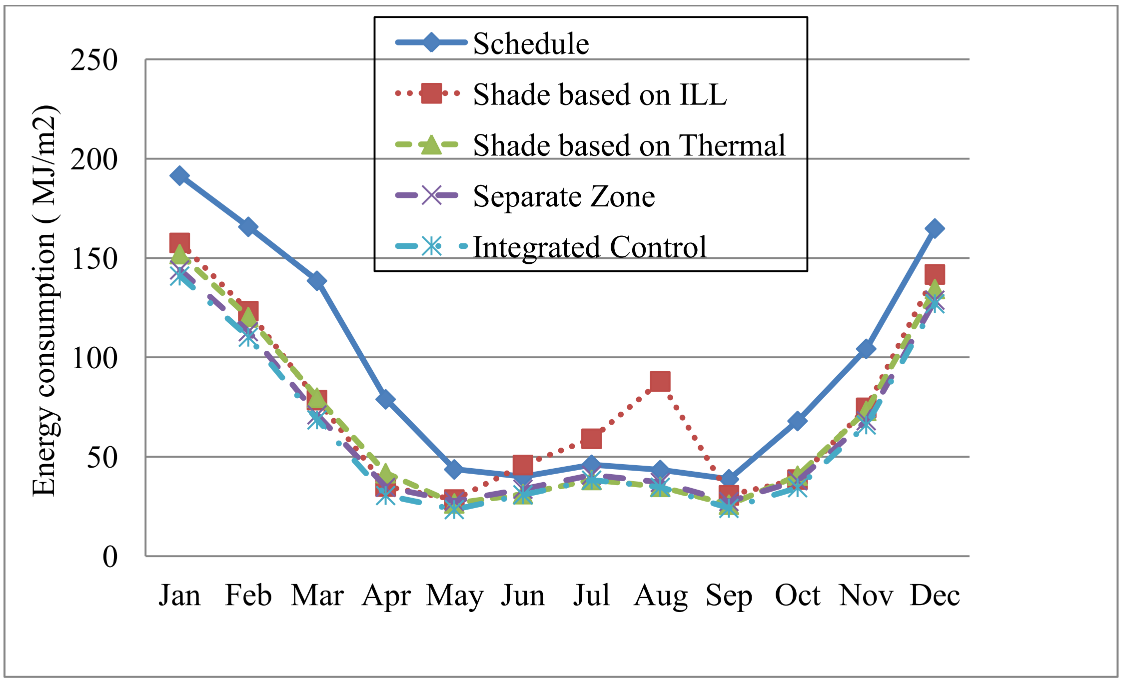


Figure 4-6: Total energy consumption for different strategies

Table 4-2: Illuminance, HVAC system and total energy consumption (MJ/m^2) for each month for different control strategies

Date	Energy	Schedule	Shade base on Illuminance	Shade base on Thermal	Individual Zone	Integrated
Jan	Light Energy	37	16	17	35	35
	HVAC Energy	153	141	134	108	105
	Total Energy	191	157	152	144	140
Feb	Light Energy	33	14	14	30	30
	HVAC Energy	132	109	105	82	80
	Total Energy	165	123	120	113	110
Mar	Light Energy	36	14	15	28	28
	HVAC Energy	102	64	64	43	40
	Total Energy	138	78	79	71	68
Apr	Light Energy	29	13	17	19	19
	HVAC Energy	49	21	23	15	10
	Total Energy	78	35	41	34	30
May	Light Energy	24	12	20	16	16
	HVAC Energy	18	15	5	10	6
	Total Energy	43	28	26	27	23
Jun	Light Energy	21	11	20	18	18
	HVAC Energy	18	34	10	15	12
	Total Energy	39	45	31	33	30
Jul	Light Energy	21	11	21	19	19
	HVAC Energy	24	47	17	20	18
	Total Energy	46	59	38	40	38
Aug	Light Energy	22	12	21	19	19
	HVAC Energy	21	75	13	17	14
	Total Energy	43	87	34	37	34
Sep	Light Energy	23	13	20	17	17
	HVAC Energy	15	17	5	10	6
	Total Energy	38	30	25	27	24
Oct	Light Energy	27	15	19	21	21
	HVAC Energy	40	23	20	16	12
	Total Energy	68	38	40	37	34
Nov	Light Energy	31	17	18	29	29
	HVAC Energy	72	57	55	38	36
	Total Energy	104	74	73	68	66
Dec	Light Energy	37	17	18	35	35
	HVAC Energy	127	123	115	93	91
	Total Energy	164	141	134	128	127

4.6 Multi-hour optimization

Optimization based on the effect of current hour control variables on future-hours energy consumption are defined as multi-hour optimization.

An important parameter in multi-hour optimization is the number of future-hours to be modelled. Considering the effect of more future hours increases the potential of energy savings, though it decreases speed of optimization significantly because of increasing optimization variables. A large number of optimization variables also increases the possibility of divergence of the optimization. As a result, it is very important to find the best possible optimization period by investigating different time periods and comparing their energy consumptions. Table 4-3 shows optimization by considering the effect of the current hour on different future-hours periods, from the next 2 hours to the next 8 hours, and optimizing the entire day at the same time. This investigation just applied to the first day of each month since multi-hour optimization is very time-consuming; these results are sufficient for studying the energy savings potential of multi-hour optimization with different time periods.

Table 4-3: Total daily energy consumption (kJ/m^2) for multi-hour optimization periods from next 2 hours to next 8 hours and optimizing entire day at same time

Optimization period					
Date	Current Hr	2hr	4hr	8hr	Entire day
1-Jan	4214	4214	4214	4214	4214
1-Feb	1628	1616	1611	1606	1606
1-Mar	2199	2189	2180	2180	2180
1-Apr	1885	1858	1834	1826	1826
1-May	937	932	927	917	915
1-Jun	835	831	827	816	813
1-Jul	904	897	891	885	885
1-Aug	899	897	895	887	887
1-Sep	936	933	927	916	916
1-Oct	669	670	669	669	669
1-Nov	1123	1122	1121	1119	1119
1-Dec	2840	2840	2840	2840	2840

The simulations show that in the multi-hour optimization, considering the next 2 hours has a small effect on building energy consumption, and it is not sufficient as a duration for multi-hour optimization.

By gradually increasing optimization duration, energy savings increase. However, the optimization time and possibility of divergence also increase. Increasing the optimization duration shows that considering the next 8 hours is sufficient for optimization of the entire day. Optimization of current hour control parameters by considering 8 future-hours energy consumption is sufficient for multi-hour optimization and most of available energy savings potential are used since current hour building condition affect on more than 8 hours is negligible. Investigating more days with higher energy savings potential shows up to 6% more energy savings by using multi-hour optimization compared to using current hour optimization.

For multi-hour optimization, time-of-use (TOU) price and energy cost should be investigated since different energy prices at different hours could affect the optimization results. TOU price was considered by defining a multiplier for different hours, as is shown in Figure 4-7.

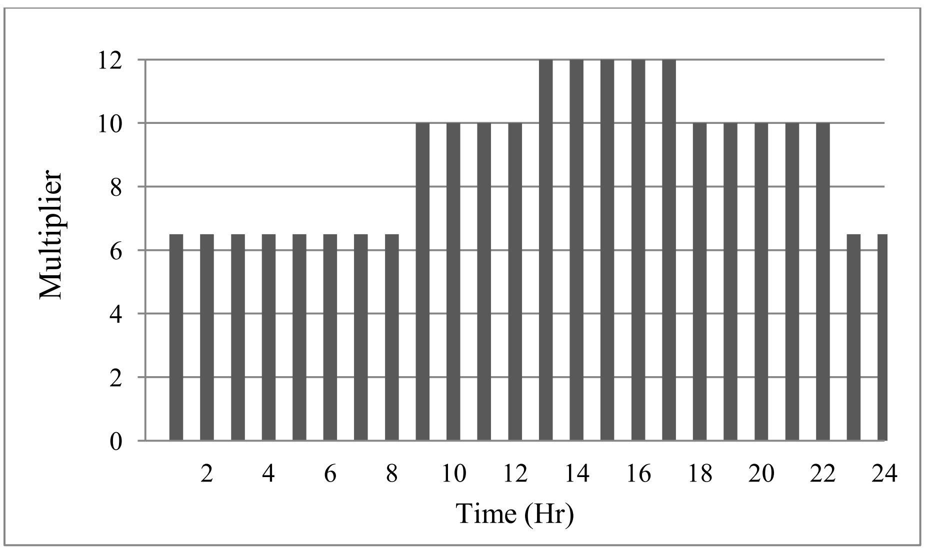


Figure 4-7: Time of use price multiplier at different hours

The simulated building energy costs are shown in Table 4-4. This table shows energy cost for optimization based on current hour and multi-hour optimization while considering the effect on the next 8 hours. Also it shows energy and cost savings for 8 hours optimization based on energy and cost.

Table 4-4: Energy cost for optimization based on current hour and multi-hour optimization and percentage of cost and energy savings

Date	Opt-current Hr	Opt-Dyn 8hr	Energy savings %	Cost savings %
1-Jan	37330	37330	0.0	0.0
1-Feb	13568	13330	1.4	1.8
1-Mar	17680	17497	0.9	1.0
1-Apr	16196	15576	3.1	3.8
1-May	9362	9053	2.2	3.3
1-Jun	8337	8077	2.2	3.1
1-Jul	8915	8661	2.1	2.9
1-Aug	8898	8702	1.2	2.2
1-Sep	9335	9068	2.0	2.9
1-Oct	6131	6127	0.1	0.1
1-Nov	9081	9045	0.3	0.4
1-Dec	24204	24204	0.0	0.0

Multi-hour optimization can save more energy and expenditure compared to current hour optimization because of two different energy storage effects. On cooling days, the building can store cooling energy during nights and early morning hours and use it during the hot hours; this process happens during May, June, July, and August. On heating days, the building can store solar heating energy from morning to noon and use this heating energy during the afternoon; this process happens during February, March, April, and November. Considering multi-hour prices for multi-hour cost optimization can lead to more savings, since considering different prices at different hours gives more flexibility to multi-hour optimization for saving energy cost by shifting energy consumption from peak price hours to off-peak.

5 Results and discussion of modification of building simulation software (DOE-2)

5.1 Developing required simulation tool by adding function to DOE-2 (application for nighttime ventilation)

The objective of this task is to assess the performance of mechanical nighttime ventilation cooling and optimize the control strategies in typical conditioned office buildings in North America. An hourly building energy simulation model, DOE-2.1E [109, 110], was used to investigate the potential for improving indoor environment and energy savings. In addition, the effect of different parameters was studied to evaluate the effectiveness of nighttime ventilation techniques as a function of flow rate and indoor-outdoor temperature difference in several climate conditions.

In this strategy next day outdoor average temperatures is predicted and based on the cooling characteristics of sample building, nighttime ventilation and duration of ventilation are determined.

Next day prediction of outdoor average temperature calculation equations [111] and decision making process (Figure 5-1) are:

$$\begin{gathered} TP_{Min} = 0.659\, T_{Min} + 0.307\, T(24) - 0.184[T(20) - T(22)] \\ TP_{Max} = T_{Max} + 0.349[T(21) - T(21\, PRE)] - 0.1[T(20) - T(22)] \end{gathered} \tag{5-1}$$

$$TP_{Ave} = (TP_{Min} + TP_{Max})/2 \tag{5-2}$$

where $T(i)$: outside temperature at hour (i), $T(i\, PRE)$: outside temperature at hour (i) for previous day, T_{Min} and T_{Max}: minimum and maximum outside temperature, and TP_{Min} and TP_{Max}: minimum and maximum predicted outside temperature for next day. Detail methodology of this research was discussed in previous chapters.

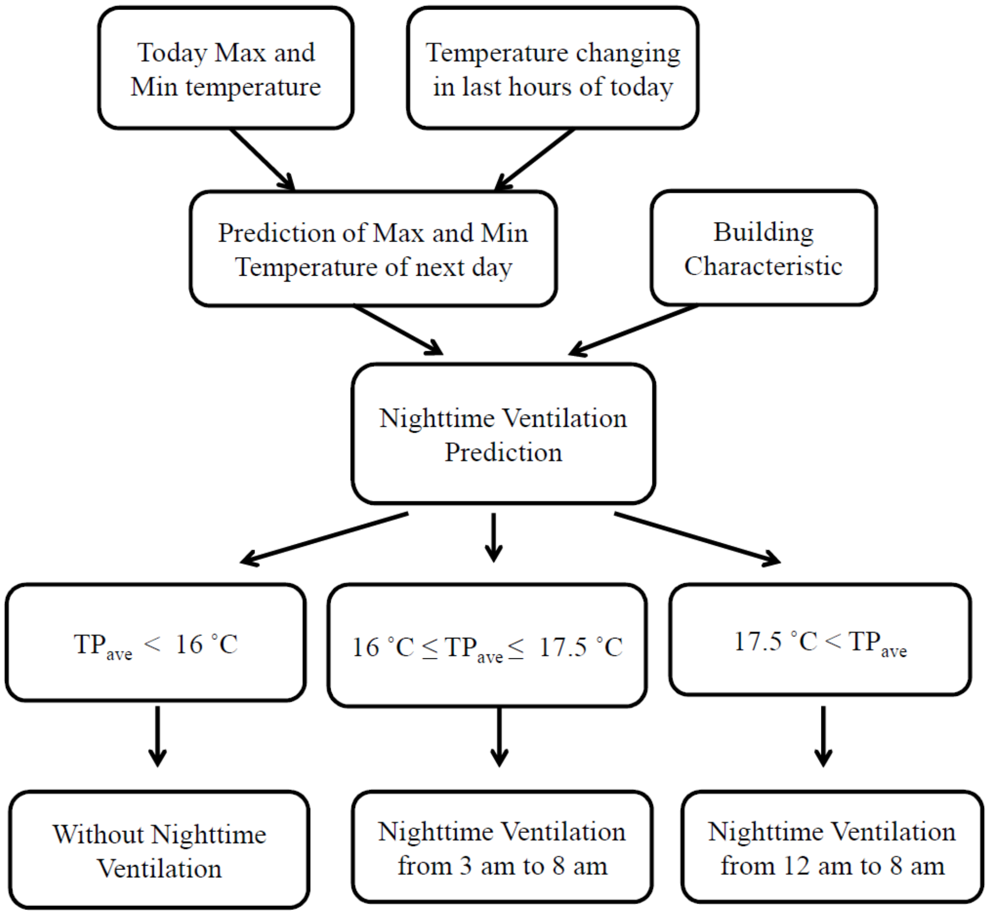


Figure 5-1: Control strategy diagram of the predictive method

Table 5-1: Annual energy consumption for basecase in investigated cities

Parameters	Montreal	Victoria	Portland
Cooling [kWh]	5289	2520	5851
Fan [kWh]	2598	2214	2606
Heat reject [kWh]	1165	549	1245
Pump & Misc [kWh]	1197	888	1087
Reheat [kWh]	3480	1458	1087
Total cooling (Cooling + Fan + Heat reject) [kWh]	9052	5283	9702
Peak cooling load [W/m^2] (Btu/hr-ft^2)	132.2 (41.9)	93.4 (29.6)	122.3 (38.7)
Zone under cooled [hours]	6	0	0

Basecase building cooling energy consumption and peak cooling load in different cities are listed in Table 5-1. Reheat system energy consumption related to resistance heating system at zone level that controls the inlet air temperature to the zone. Heat rejects energy consumption related to electrical energy consumption of condenser, fans and pumps in cooling towers system.

The occupancy comfort can be investigated based on the zone under cooled hours. This parameter represents the total hours when the inside temperature of the building exceeds the cooling set-point during a year.

5.1.1 The effect of schedules on nighttime ventilation

The effectiveness of the scheduled-driven ventilation is very sensitive to the assumption of what is the summer period. This is considered as a severe disadvantage for this strategy. In contrast, with the predictive algorithm, there is no need to pre-define a summer period schedule. This strategy automatically decides about using nighttime ventilation based on the prediction of next day temperature. The simulated cooling energy consumptions using the scheduled-driven strategy with different summer periods are shown in Table 5-2. The results show that the optimal cooling energy savings is 7.7% for the best defined summer period. Adding two weeks to this period, savings reduces to 7.4% approximately equal to the amount of savings by using the predictive method in Montreal. The amount of savings decreases to 6.5% by adding two more weeks.

Table 5-2: The effect of scheduled nighttime ventilation for different periods in Montreal (DT=5.5°C, Flow rate= 1.4m^3/s, FW=490kg/m^2)

Parameter	Basecase	Predictive method	Scheduled ventilation during summer				
		Entire Year	1 JUN to 31 AUG	24 MAY to 7 SEP	17 MAY to 14 SEP	10 MAY to 21 SEP	1 MAY to 31 SEP
Cooling [kWh]	5289	4365	4397	4354	4324	4317	4298
Fan [kWh]	2598	2986	2915	2987	3106	3229	3376
Heat reject [kWh]	1165	1039	1045	1039	1031	1029	1023
Total Cooling (Cooling+ Fan + Heat reject) [kWh]	9052	8390	8357	8380	8461	8575	8697
Savings % (Cooling+ Fan +Heat reject)	0	7.3	7.7	7.4	6.5	5.3	3.9
Savings % (Total)	0	4.7	5	4.7	3.9	2.8	1.5
Peak cooling load [W/m^2] (Btu/hr-ft^2)	132.2 (41.9)	128.7 (40.8)	128.7 (40.8)	128.7 (40.8)	128.7 (40.8)	128.7 (40.8)	128.7 (40.8)
Zone under cooled (hours)	6	2	2	2	2	2	2

Table 5-3: The effects of nighttime ventilation fan flow rate on scheduled ventilation during summer, predictive method, and pre-cooling integrated with predictive method for Montreal and Portland. The simulations are performed for an indoor-outdoor temperature difference (ΔT) of 5.5°C and floor weight of 490kg/m^2

Location	Parameter	Basecase	Ventilation rate [m^3/s]									
			Schedule ventilation during summer				Predictive method			Pre-cooling+Nighttime cooling		
			0.47	0.94	1.4	1.9	0.47	0.94	1.4	0.47	0.94	1.4
Montreal	Cooling [kWh]	5289	4845	4522	4397	4110	4829	4495	4365	4622	4332	4105
	Fan kWh	2598	2681	2848	2915	3332	2707	2903	2986	2756	2931	3180
	Total cooling (Cooling+Fan+Heat reject) [kWh]	9052	8633	8430	8357	8438	8641	8454	8390	8470	8318	8309
	Savings % (Cooling + Fan+Heat reject)	0	4.6	6.9	7.7	6.8	4.5	6.6	7.3	6.4	8.1	8.2
	Peak cooling load [W/m^2] (Btu/hr-ft^2)	132.1 (41.9)	129.3 (41)	127.4 (40.4)	125.2 (39.7)	123.9 (39.3)	129.3 (41)	127.3 (40.3)	125.2 (39.7)	129.3 (41)	127.8 (40.5)	126.6 (40.1)
	Zone under cooled [hours]	6	2	2	1	1	2.0	2.0	1.0	24.0	19.0	17.0
Portland	Cooling [kWh]	5851	5367	5023	4764	4585	5268	4853	4540	4775	4433	4186
	Fan [kWh]	2606	2661	2824	3064	3341	2698	2916	3229	2712	2894	3160
	Total cooling (Cooling + Fan + Heat reject) [kWh]	9702	9199	8967	8911	8983	9126	8871	8828	8557	8355	8343
	Savings % (Cooling + Fan+Heat reject)	0.0	5.2	7.6	8.2	7.4	5.9	8.6	9.0	11.8	13.9	14.0
	Peak cooling load [W/m^2] (Btu/hr-ft^2)	122.2 (38.8)	117.9 (37.4)	115 (36.5)	112.4 (35.6)	110.4 (35.0)	117.9 (37.4)	115 (36.5)	112.4 (35.6)	101 (32.0)	98.6 (31.3)	97.5 (30.9)
	Zone under cooled [hours]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0

5.1.2 Nighttime ventilation fan flow rate

The effect of different nighttime ventilation fan flow rates during summer with the scheduled-driven, the predictive method and with the integrated pre-cooling and predictive method for Montreal and Portland are shown in Table 5-3. The results show that increasing fan flow rate reduces cooling energy consumption, but increases fan energy consumption. Moreover, results of the energy savings illustrate that there is fairly flat total energy consumption in the range of 1 m^3/s to 1.5 m^3/s (2200-3200 CFM) with optimal flow rate near 1.4 m^3/s (3000 CFM) (Figure 5-2). Simulation for Montreal shows that the savings at 1.4 m^3/s (3000 CFM) with scheduled ventilation during summer is 7.7% and with the predictive method is 7.3%. The predictive method, which works during the entire year, shows less savings as a result of incorrect prediction about the next day's need for cooling. For Portland the simulation results show an inverse trend; savings with the predictive method is higher than with scheduled ventilation. The predictive nighttime ventilation worked better in Portland since its weather conditions are fairly smooth in transition seasons. Whereas, the unpredictable weather condition of Montreal makes the predictive nighttime ventilation less efficient.

With integration of pre-cooling and nighttime ventilation more energy can be saved. Whereas, the hours of zone being under-cooled are increased using this combination method. The increased hours of being under-cooled affect the occupant comfort, yet still in an acceptable range. Combined nighttime ventilation and pre-cooling reduced peak cooling load up to 20%.

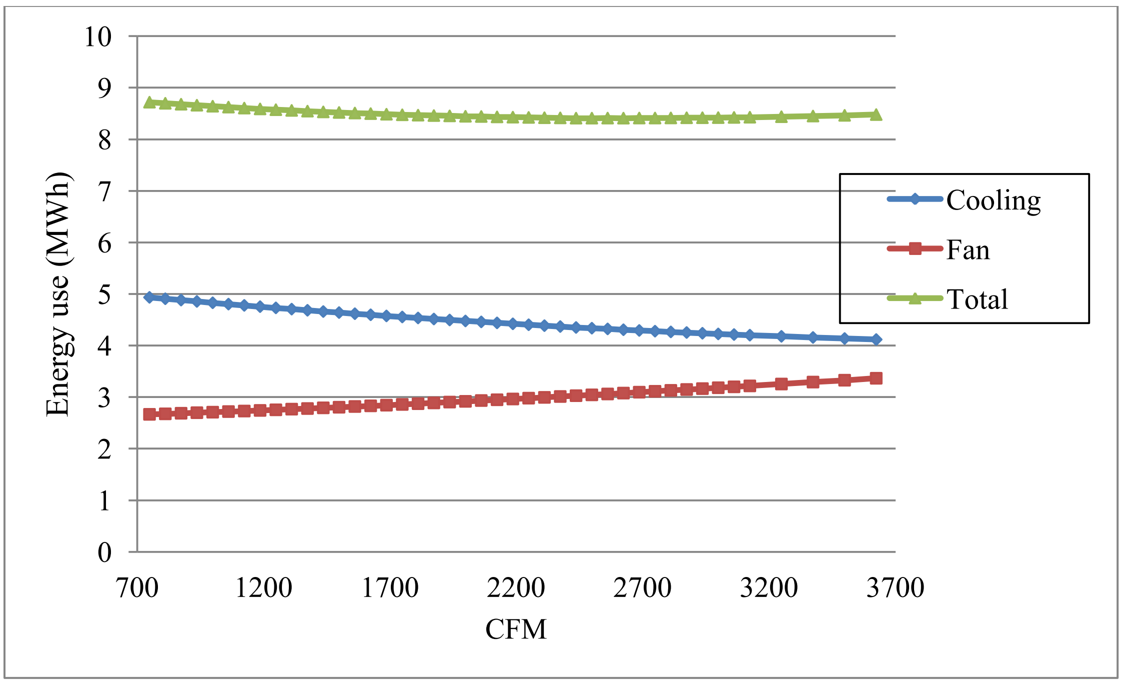


Figure 5-2: Energy use for Cooling, Fan and Total (cooling + fan + heat reject) with different air flow rates (CFM) in Montreal

5.1.3 Thermal mass effect

Table 5-4 shows the effect of building thermal mass on nighttime ventilation. Here, three different floor weights with three different strategies are considered for Montreal. These strategies are *without* nighttime ventilation (*WO* NV), *with* scheduled ventilation during summer (*W* NV), and *with* predictive method (*W* FUNC). For very low thermal mass there was not any savings, as was expected. It is possible to see that for high thermal mass, the predictive method works better than scheduled ventilation during the summer.

Table 5-4: The effect of building thermal mass on nighttime ventilation for three different floor weights with three different strategies in Montreal (ΔT=5.5°C, Flow rate= 0.47m^3/s)

Parameter	49kg/m^2 (10 lb/ft^2)			490kg/m^2 (100 lb/ft^2)			980kg/m^2 (200 lb/ft^2)		
	WO NV	W NV	W FUNC	WO NV	W NV	W FUNC	WO NV	W NV	W FUNC
Total cooling (Cooling+ Fan+Heat reject) [kWh]	10081	10072	10142	9052	8633	8641	8811	8430	8425
Savings % (Cooling+Fan+ Heat reject)	0.0	0.1	-0.6	0.0	4.6	4.5	0.0	4.3	4.4
Peak cooling load [W/m^2] (Btu/hr-ft^2)	122.2 (38.7)	122.2 (38.7)	124.5 (39.4)	132.2 (41.9)	130.2 (41.2)	129.4 (41.0)	125.6 (39.8)	123.9 (39.3)	123.1 (39.0)
Zone under heated [hours]	346	425	704	49	49	49	35	35	35
Zone under cooled [hours]	1	1	2	6	3	2	3	3	2

W-With, WO-Without, NV-Nighttime Ventilation, FUNC-Predictive Function

5.1.4 Temperature difference between inside and outside air

The temperature of outside air that the ventilation fan brings in during the night for cooling the building has an important effect on effectiveness of nighttime ventilation. When the temperature difference between inside and outside air is low, the brought in air is not useful in cooling the building. In this case, the ventilation fan energy use increases total energy consumption, while having little effect on cooling the building. On the other hand, if outside air is just brought in when its temperature is significantly lower than the inside air, the hours of nighttime ventilation decrease and a significant amount of cooling potential that exists in the outside air is not utilized. So, an optimal situation should be found between these two conditions in order to reach the maximum energy savings. Table 5-5 shows the building energy consumption with different temperature differences between outside and inside air for nighttime ventilation. According to these results, optimum savings for Montreal happens when the temperature difference is approximately 5.5 °C (10 °F) (Figure 5-3). It is possible to see that cooling energy consumption first decreases with increasing temperature difference from 0.5 to 4.5 °C (1 to 8 °F), while this trend changes by continuing to increase the temperature difference.

Table 5-5: The effect of ventilation temperature difference between inside and outside air in Montreal (Flow rate= 1.4m^3/s, FW=490kg/m^2)

Parameter	Scheduled ventilation during summer			Predictive method			
	2.8°C (5.0°F)	5.5°C (10.0°F)	8.3°C (15.0°F)	2.8°C (5.0°F)	5.5°C (10.0°F)	8.3°C (15.0°F)	11.1°C (20°F)
Cooling [kWh]	4274	4397	4697	4238	4365	4677	4966
Fan [kWh]	3077	2915	2710	3164	2986	2748	2632
Total cooling (Cooling+ Fan+Heat reject) [kWh]	8372	8357	8501	8418	8390	8515	8725
Savings % (Cooling+Fan+Heat reject)	7.5	7.7	6.1	7.0	7.3	5.9	3.6
Savings % (Total)	4.8	5.0	3.9	4.5	4.7	3.8	2.3
Peak cooling load [W/m^2] (Btu/hr-ft^2)	125.3 (39.7)	128.6 (40.8)	131.7 (41.8)	125.3 (39.7)	128.6 (40.8)	154.5 (49.0)	132.0 (41.8)
Zone under cooled [hours]	1.0	2.0	4.0	1.0	2.0	4.0	5.0

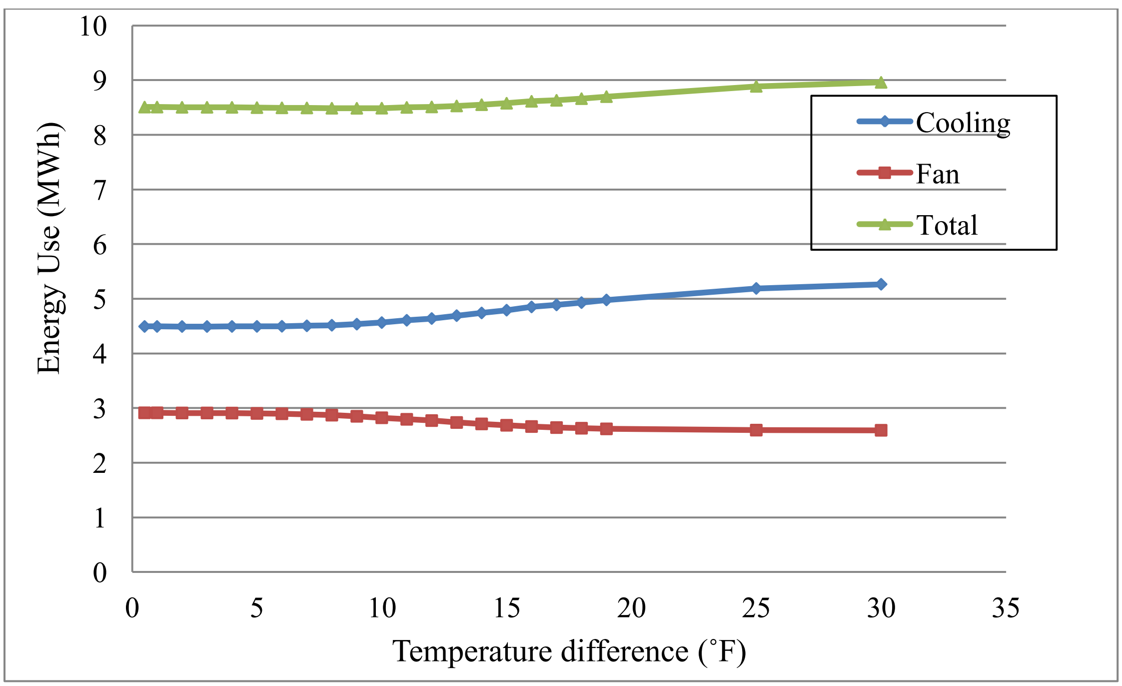


Figure 5-3: Energy use for Cooling, Fan and Total (cooling + fan + heat reject) for different indoor-outdoor temperature difference in Montreal

5.1.5 Pre-cooling

Pre-cooling is another strategy for reducing the energy consumption and especially reducing the peak load in the building. This strategy works by changing the cooling set-point during the day. In the morning, when the outside air temperature is low, the cooling set-point is set to a lower temperature than the regular value. So, the building will store some cooling energy. In the afternoon, when the outside air temperature is at the highest, more cooling is required for the building. Consequently, the set-point is increased to reduce the amount of cooling energy consumption. The stored cooling energy in the building mass is then used in the afternoon. In order to find the minimum cooling energy consumption, various pairs of set-points with the same daily average were investigated. The results, illustrated in Table 5-6 show the pre-cooling strategy that kept the set-point temperature till afternoon and changed it at peak hour could save more energy than the other strategies. This strategy, though, has a higher peak load since the peak hour at the specific day happened at hour 14.

Table 5-6: The HVAC electricity use for different Pre-cooling Methods in Portland

Parameter	Basecase	Pre-Cooling (Time)(Temp. °C) (Time)(Temp. °C)		
		(9-12)(24) (13-18)(26.6)	(9-13)(24.4) (14-18)(26.6)	(9-14)(24.7) (15-18)(26.6)
Cooling [kWh]	5851	5434	5264	5202
Fan [kWh]	2606	2653	2677	2685
Total Cooling (Cooling+Fan +Heat reject) [kWh]	9702	9294	9070	9018
Savings % (Cooling+Fan+Heat reject)	0	4.2	6.5	7.1
Peak cooling load [W/m^2] (Btu/hr-ft^2)	122.3 (38.8)	116.1 (36.8)	105.7 (33.5)	107.6 (34.1)
Zone under cooled [hours]	0	10	26	60

5.1.6 Effect of climate on nighttime cooling and pre-cooling

Results of the simulations for nighttime ventilation and pre-cooling show up to 15% savings for cooling and ventilation energy consumption in the three climates simulated (Table 5-7). The highest savings is achieved in Portland and lowest in Montreal. Because of the unpredictable weather condition of Montreal as well as its cold weather, the scheduled ventilation strategy works better than the predictive method. On the other hand, in Portland and Victoria, the predicted ventilation strategy always leads to more energy savings. By adding pre-cooling to nighttime ventilation, energy savings increased significantly, especially when lower nighttime ventilation flow rate was used.

Table 5-7: Energy savings with different strategies for three different flow rates in investigated cities (DT=5.5°C, FW=490kg/m^2)

Cities	Strategy	Flow rate		
		0.47 m^3/s (1000 CFM)	0.94 m^3/s (2000 CFM)	1.4 m^3/s (3000 CFM)
Montreal	Scheduled ventilation during summer	4.6	6.9	7.7
	Predictive method	4.5	6.6	7.3
	Pre-cooling + Night-time cooling	6.4	8.1	8.2
Victoria	Scheduled ventilation during summer	6.2	7.9	6.1
	Predictive method	6.3	8.0	6.2
	Pre-cooling + Night-time cooling	11.2	11.7	9.4
Portland	Scheduled ventilation during summer	5.2	7.6	8.2
	Predictive method	5.9	8.6	9.0
	Pre-cooling + Night-time cooling	11.8	13.9	14.0

5.1.7 Roof insulation

In the above simulations, the roof insulation was set at R-03 (h ft^2 F/Btu in) that is very low insulation. In order to investigate the effect of the roof insulation on the effectiveness of the nighttime ventilation strategies, we simulated our building with different roof insulations. These simulation results (Table 5-8) illustrated that the higher the roof insulation the higher the energy savings (both in absolute and relative terms).

In Montreal, the scheduled ventilation resulted in more savings compared to the predictive model. As the roof insulation increases, the difference between the savings estimated by the scheduled and the predictive model strategies become less significant. For Portland and Victoria, the energy savings using the predictive method becomes even higher than that of the scheduled-driven strategy. In addition the predictive nighttime ventilation worked better in Portland since its weather conditions are fairly smooth in transition seasons. Whereas, the unpredictable weather condition of Montreal makes the predictive nighttime ventilation less efficient. Based on the control strategies simulated for the office buildings in the three cities, it is found that most energy savings are achieved when the building is cooled by nighttime ventilation integrated with pre-cooling.

Table 5-8: The effect of roof insulation in nighttime ventilation for three different cities with three different strategies in Montreal (DT=3°C, Flow rate= 1.4m^3/s, FW=490kg/m^2)

Location	Parameter	R-03			R-13			R-30		
		Basecase	Scheduled ventilation	Predictive method	Basecase	Scheduled ventilation	Predictive method	Basecase	Scheduled ventilation	Predictive method
Montreal	Cooling [kWh]	5289	4397	4365	5032	3901	3856	5003	3811	3761
	Fan [kWh]	2598	2915	2986	2531	2938	3016	2494	2880	2950
	Heat reject [kWh]	1165	1045	1039	1088	930	923	1090	906	899
	Total cooling [kWh]	9052	8357	8390	8651	7769	7795	8587	7597	7610
	Cooling Savings [kWh]	0	-695	-662	0	-882	-856	0	-990	-977
	Cooling Savings %	0.0	7.7	7.3	0.0	10.2	9.9	0.0	11.5	11.4
Portland	Cooling [kWh]	5851	4764	4540	5530	4362	4107	5453	4267	4002
	Fan [kWh]	2606	3064	3229	2652	3037	3164	2678	3045	3154
	Heat reject [kWh]	1245	1083	1059	1154	989	966	1117	958	938
	Total cooling [kWh]	9702	8911	8828	9336	8388	8237	9248	8270	8094
	Cooling Savings [kWh]	0	-791	-874	0	-948	-1099	0	-978	-1154
	Cooling Savings %	0.0	8.2	9.0	0.0	10.2	11.8	0.0	10.6	12.5
Victoria	Cooling [kWh]	2520	1775	1762	2395	1603	1590	2368	1564	1550
	Fan [kWh]	2214	2745	2750	2283	2724	2727	2332	2738	2741
	Heat reject [kWh]	549	443	442	503	405	404	486	394	393
	Total cooling [kWh]	5283	4963	4954	5181	4732	4721	5186	4696	4684
	Cooling Savings [kWh]	0	-320	-329	0	-449	-460	0	-490	-502
	Cooling Savings %	0.0	6.1	6.2	0.0	8.7	8.9	0.0	9.4	9.7

5.2 Predicting nighttime fan flow rates with neural network

Neural network developments and applications, in addition to detailed structure of trained NN, are explained in previous chapters. Input parameters and numbers of neurons in the hidden layer are two effective categories that need to be investigated. Figure 5-4 shows the results of MSE between simulated and predicted fan flow rate fraction for different types of inputs for neural network. Three different types of inputs were investigated: 1) hourly inputs, which include hourly outdoor temperature and hourly indoor temperature; 2) daily inputs, which include diurnal average and range temperature and night average temperature; 3) combination of daily and hourly inputs. The fan flow rate fraction is a number between 0 and 1, as a result, combination of daily and hourly inputs with MSE less than 0.035 are suitable inputs for the neural network.

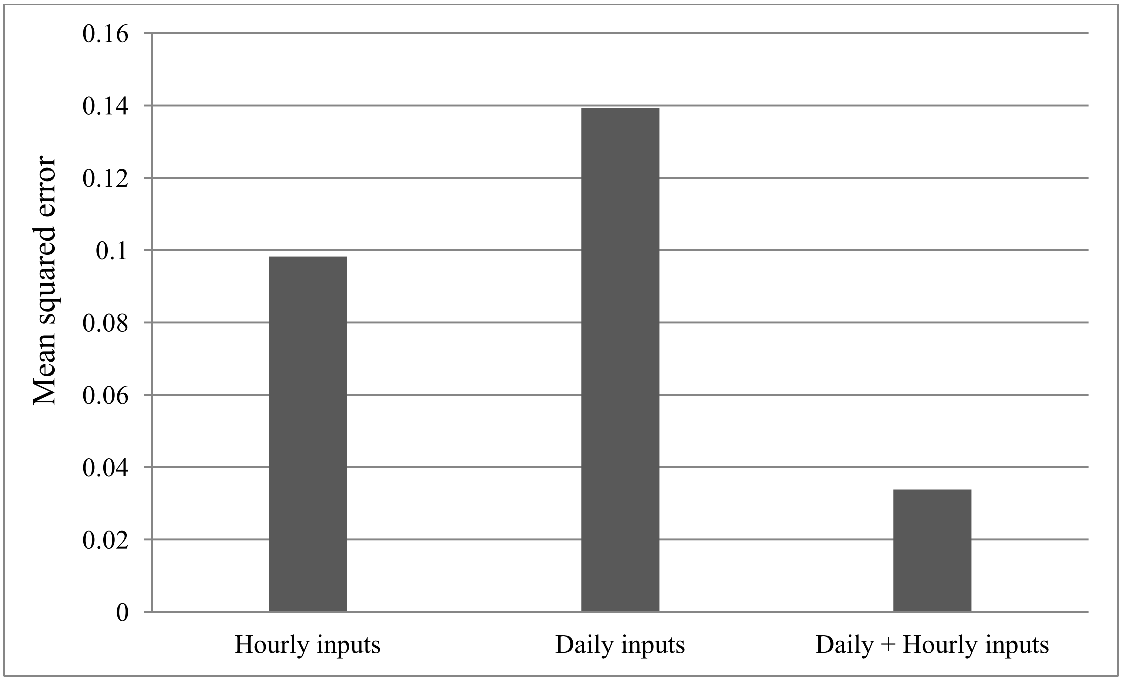


Figure 5-4: MSE of predicted fan flow rate fraction (a number between 0 and 1) versus different types of inputs for neural network

The results show that using both daily and hourly inputs are necessary for developing accurate neural network.

The number of neurons in the hidden layer should be adequate to the complexity of the problem data. Underfitting occurs when neurons in the hidden layers are too few to appropriately detect the relation in a complicated data set. Overfitting may occur when unnecessary too many neurons are present in the network, which means that the neural networks over-estimate the complexity of the target problem. It can leads to significant deviation in predictions. As a result, determining the proper number of hidden neurons to prevent overfitting and underfitting is critical in using NN [118].

Figure 5-5 shows MSE versus number of neurons in the hidden layer. According to the results, hidden layer with 18 neurons was picked since it has the minimum MSE.

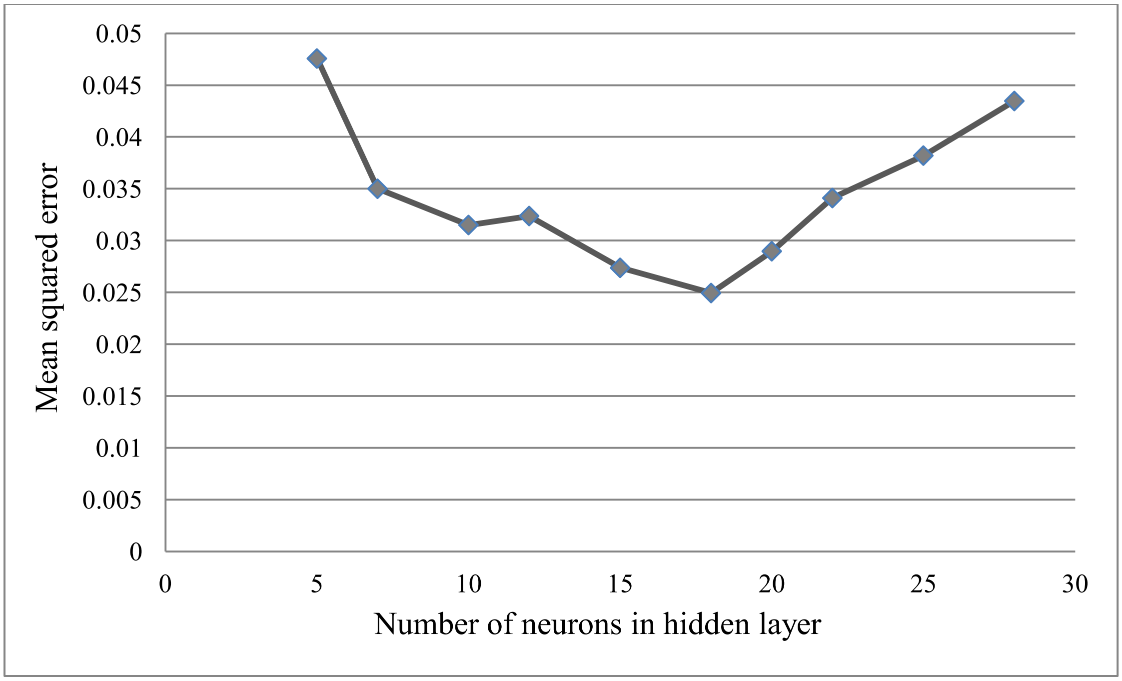


Figure 5-5: MSE versus number of neurons in hidden layer

A developed neural network based on daily and hourly inputs with 18 neurons in the hidden layer trained and tested with results of fan flow rate optimization. This trained NN can be used for prediction of fan flow rate fraction for other days without using optimization, which is time consuming. Figure 5-6 shows good agreement between predicted results of fan flow rate and optimization results for the same hour.

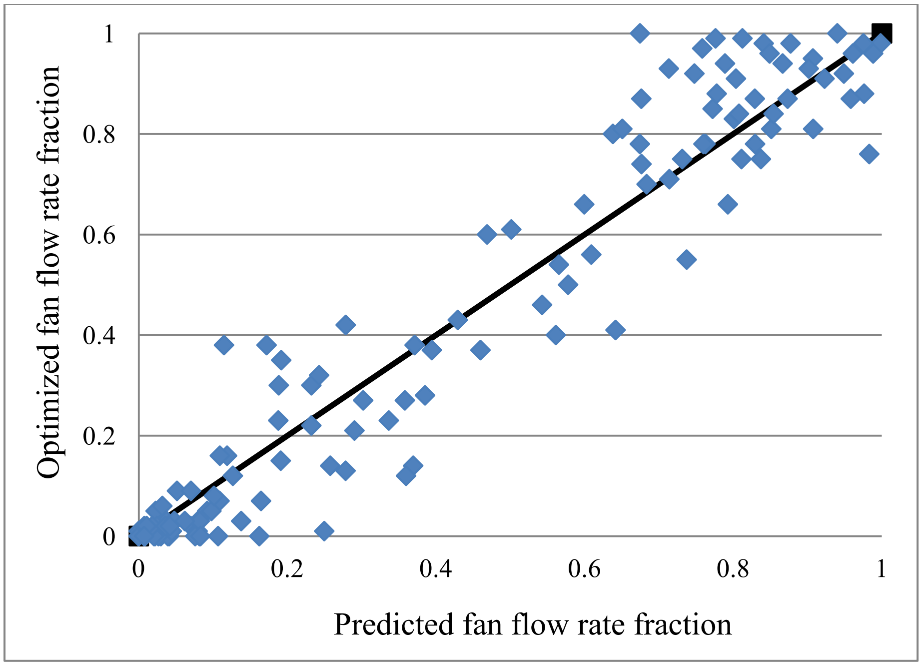


Figure 5-6: Neural Network results of fan flow rate fraction compare to optimization results

5.3 Investigation of shading and daylighting

Shading devices can improve the light distribution in the room and they are flexible and can be removed when the outdoor light level is low. Also they can adjust the window heat losses and gains through changing the window U-value. Thus, the potential for daylight and solar heat gain utilization is significant with shading devices. Most of the previous research about solar shading devices has focused on the energy aspect. Only a few studies have considered the impact of shading devices on daylighting and the visual (comfort) aspect [114]. For better understanding of shading effects, in this section the shading effect on daylight savings and energy consumption are investigated in a heating day at November 18 hour 9 (Figure 5-7 and Figure 5-8). The results show that closing the shade up to 70% did not affect lighting energy consumption in this specific hour since outdoor illuminance was much higher than the room illuminance set-point. Also the results for heating energy consumption show that heating energy consumption decreases by closing the shade since it decreases solar heat gain and heat transfer from the window. When investigating the same parameters in different hours and different outdoor conditions, the results show that there could be an optimal position of the shade that keeps the heat gain at a minimum amount while still taking advantage of daylighting.

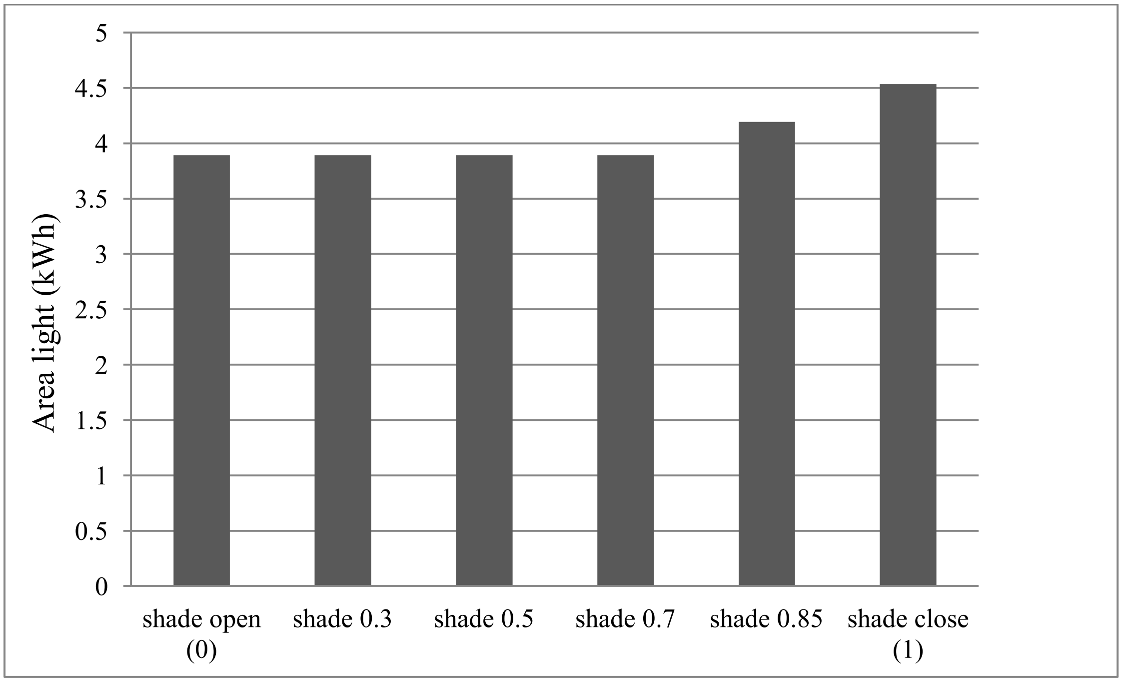


Figure 5-7: Effect of shade position on light power for November 18 hour 9

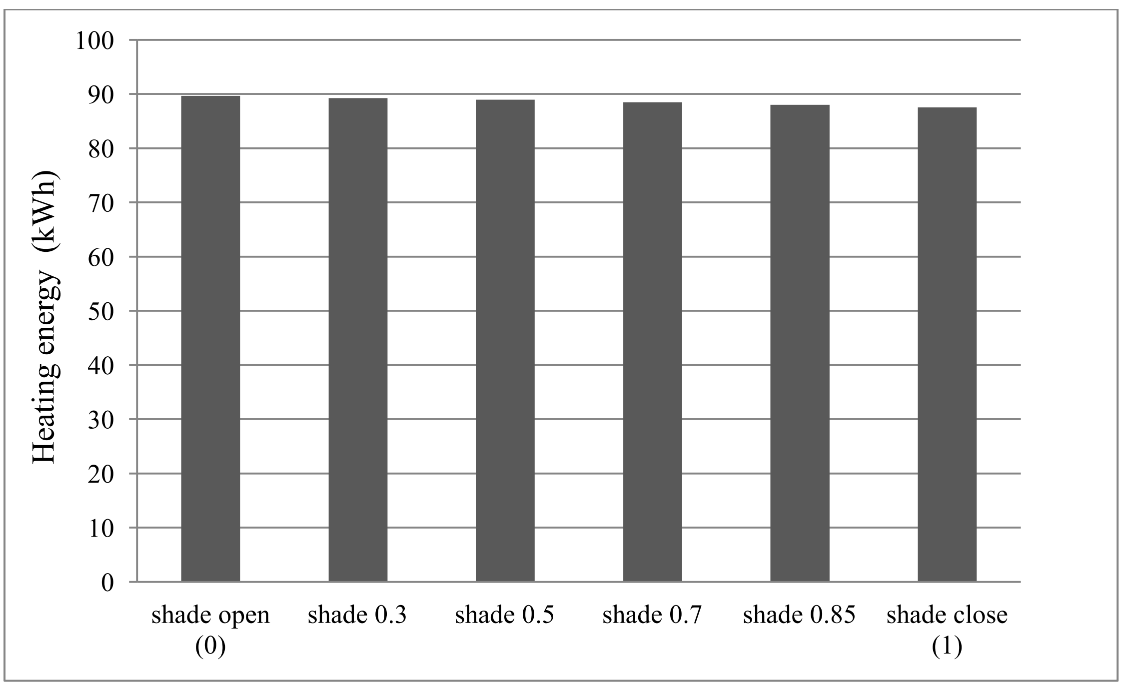
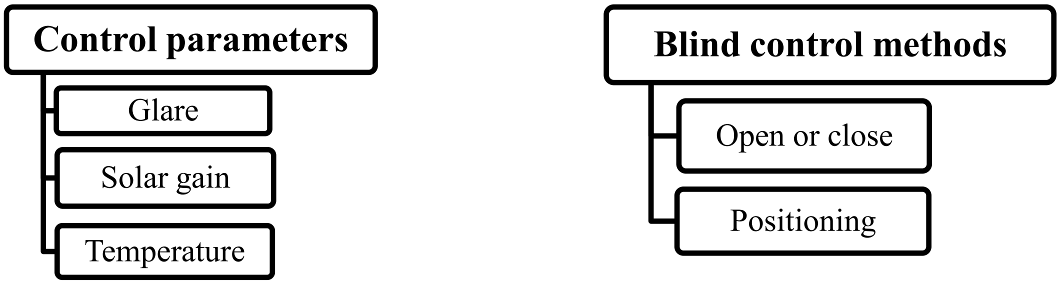


Figure 5-8: Effect of shade position on heating energy for November 18 hour 9

In addition, the potential of daylight as a natural renewable source of energy in providing the required illumination requirements and reducing energy consumption in a typical office building is studied. To investigate the effect of daylighting in building energy consumption, DOE-2 building simulations is used. DOE-2 uses a daylight factor for calculation of daylighting by integrating transmitted luminous flux over the area of each window (or skylight). Interior illuminance at user-selected room locations is calculated for a standard overcast sky and for clear sky conditions with 20 different sun positions. Dividing the interior illuminance by the corresponding exterior illuminance gives daylight factors that are stored for later interpolation in the hourly simulation. Analogous factors for the discomfort of glare from each window are also calculated and stored for each sun angle and sky condition. The hourly illuminance and glare contribution from each window are found by interpolating the stored daylight factors using the current hour sun position and cloud cover, then multiplying by the current-hour exterior horizontal illuminance. If the glare-control option has been specified, the program automatically closes window blinds or drapes in order to decrease glare below a pre-defined comfort level. A similar option uses window shading devices to automatically control solar gain. One disadvantage of DOE-2 in daylight modeling is that it cannot control the blind position according to glare and heat gain, so for solving this problem some functions are added to the source code of DOE-2.This function calculates new shading coefficients for solar radiation and illuminance transmittance considering shade position and modified close shade coefficients based on these new coefficients.

$$\begin{cases} q_x = q_c\, x + \; q_o\, (1-x) \\ Il_x = Il_c\, x + \; Il_o\, (1-x) \end{cases} \begin{cases} x = 1\; close\ shade \\ x = 0\; open\ shade \end{cases} \tag{5-3}$$

The control parameters and results of energy saving for using default control method of DOE-2 and the positioning control method are shown in Figure 5-9. The results show 25% energy savings for the default control method and 34% energy savings for the blind positioning control method.



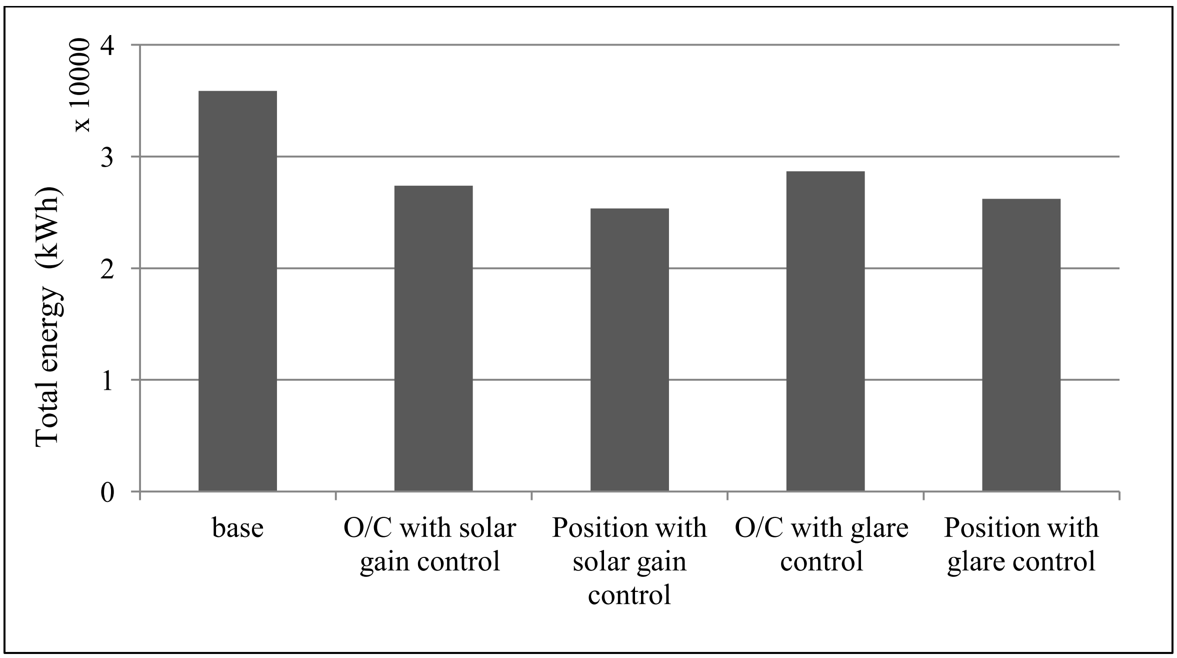


Figure 5-9: The control parameters and results of energy saving for using open or close control method of DOE-2 and positioning control method

6 Results and discussion of integration of MATLAB and DOE-2

An integrated building control optimization tool is developed based on connecting a genetic algorithm as an optimization tool in MATLAB, and DOE-2 as a building energy and cost calculation software. Details of this integration were discussed in chapter 3. The developed optimization tool is evaluated by investigating its application to nighttime ventilation and shading position optimization. Thereafter, rule-based decision making before optimization and local search after optimization are added to the optimization tool to make it faster. Finally the integrated optimization tool is applied to the whole sample building for optimization of all indoor controllable parameters, including: indoor temperature, shade position, artificial light power, and outdoor air ventilation rate. In this chapter results of applying the integrated optimization tool in nighttime ventilation and shade position optimization are discussed. Also, development and evaluation of different methods for increasing speed of optimization are investigated. In addition, results of whole-building optimization are presented.

6.1 Integrating MATLAB with DOE-2 (application for nighttime ventilation)

Nighttime fan flow rates optimization was applied for five hours before working hours during the summer (Jun, July and August) in Montreal. The results for days with energy savings during summer are listed in Table 6-1. These results show total energy savings up to 8% and cooling energy saving up to 23%. These savings happened on a day with high diurnal temperature range and average temperature near 17 ˚C.

Optimization of nighttime ventilation fan flow rates with direct connection of DOE-2 and MATLAB is very time consuming as a result optimization just applied to some specific days with outdoor condition suitable for nighttime ventilation. These sample days are chosen based on their daily average and range outdoor temperature.

The results show less than 10% total energy savings since using nighttime ventilation increases building ventilation fan energy consumption that decreases total energy savings.

The results for total-building and cooling-energy consumption with and without nighttime ventilation during some days of summer are shown in Figure 6-1 and Figure 6-2.

Table 6-1: Daily weather conditions and optimization results during summer in Montreal

Day No.	Date	Diurnal ave temp.	Diurnal temp. range	Night ave temp.	Ave fan flow rate fraction	Energy savings (kWh)	Cooling savings (kWh)	% Energy savings	% Cooling savings
1	8-Jun	20.2	13.9	14.0	0.4	2.1	6.7	2.0	9.7
2	10-Jun	23.4	14.4	17.4	0.3	0.8	4.5	0.5	4.2
3	13-Jun	13.6	8.9	10.0	0.3	1.2	1.1	1.9	6.2
4	14-Jun	17.1	16.1	10.2	0.6	7.8	13.6	8.1	23.0
5	15-Jun	19.9	15.0	13.3	0.7	5.5	13.8	4.3	16.6
6	16-Jun	20.0	8.3	16.6	0.4	1.9	7.3	1.6	10.1
7	17-Jun	22.1	11.7	17.1	0.4	0.1	5.3	0.1	5.8
8	22-Jun	19.4	11.1	14.8	0.4	1.4	5.8	1.4	9.0
9	23-Jun	20.1	12.8	14.1	0.5	4.5	10.6	3.9	14.2
10	24-Jun	22.5	15.6	15.7	0.5	2.4	10.0	1.7	10.5
11	28-Jun	16.6	15.0	10.0	0.1	1.1	2.4	1.7	6.3
12	29-Jun	16.7	9.4	13.6	0.5	3.7	8.7	4.9	22.1
13	6-Jul	17.4	8.9	14.0	0.3	1.2	4.3	1.1	6.7
14	7-Jul	19.3	11.1	14.7	0.5	2.8	8.3	2.2	10.8
15	8-Jul	20.1	10.6	15.7	0.4	1.9	6.4	1.4	7.2
16	14-Jul	20.6	11.1	16.7	0.5	1.3	7.6	1.1	10.2
17	22-Jul	15.7	9.4	13.0	0.2	0.4	2.3	0.5	6.2
18	27-Jul	17.2	13.9	10.8	0.4	1.6	6.2	2.1	14.2
19	28-Jul	20.0	12.2	14.7	0.5	1.7	7.9	1.5	10.8
20	29-Jul	21.3	8.9	17.3	0.4	1.7	6.2	1.3	7.4
21	5-Aug	19.9	12.2	14.3	0.4	2.5	7.3	2.2	10.4
22	11-Aug	20.4	12.8	14.3	0.5	4.4	11.3	3.2	12.8
23	12-Aug	20.0	11.1	16.2	0.5	2.5	9.1	1.9	10.9
24	18-Aug	18.8	10.6	15.1	0.2	0.6	3.1	0.7	5.4
25	19-Aug	22.2	12.2	16.4	0.4	0.6	5.9	0.4	6.5
26	22-Aug	19.9	12.2	14.7	0.9	7.3	15.5	4.4	15.4
27	23-Aug	18.8	8.3	16.7	0.4	0.6	6.4	0.5	8.9
28	25-Aug	15.2	11.7	9.8	0.1	0.8	1.6	1.7	5.9
29	26-Aug	15.9	12.8	11.9	0.4	1.3	6.5	2.1	19.7
30	30-Aug	18.5	11.1	13.8	0.4	1.1	6.2	1.4	12.8

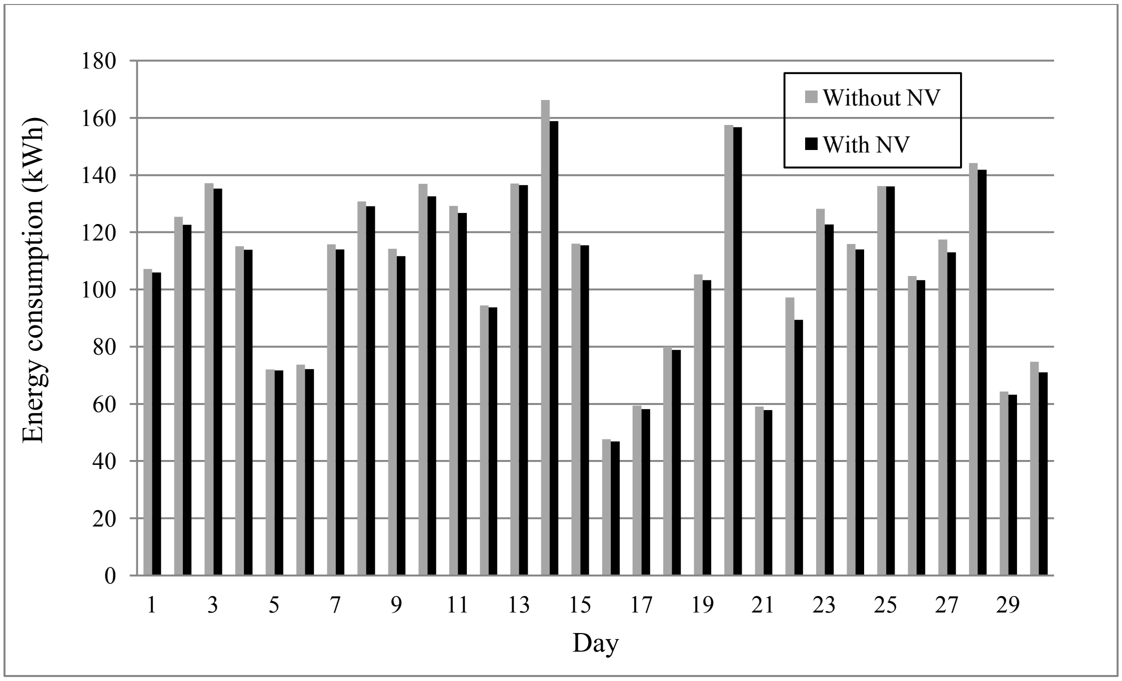


Figure 6-1: Building total energy consumption with and without nighttime ventilation during summer in Montreal

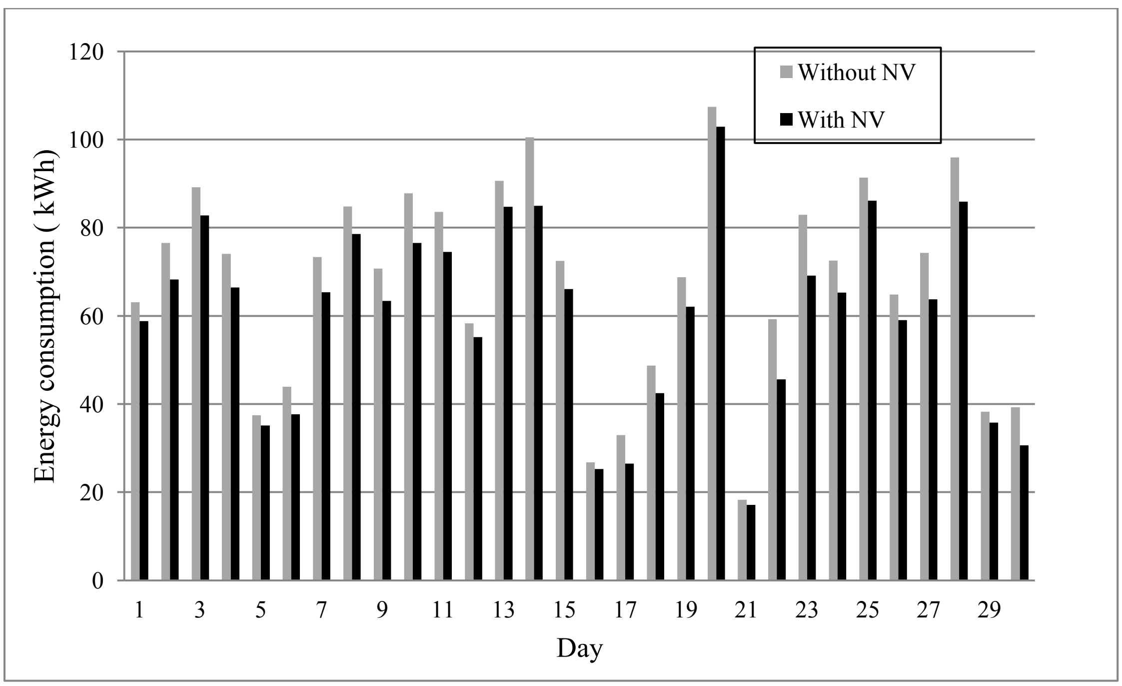


Figure 6-2: Building cooling energy consumption with and without nighttime ventilation during the summer in Montreal

6.1.1 Diurnal outdoor air temperature

Figure 6-3 shows total energy savings percentage verses outdoor average and diurnal temperature range. Based on the results at constant outdoor average temperature, energy savings increase when there is a higher temperature range. Also the results show that higher energy savings happen at outdoor average temperatures between 15 ˚C and 22 ˚C and energy savings decrease when outdoor average temperature is out of this range.

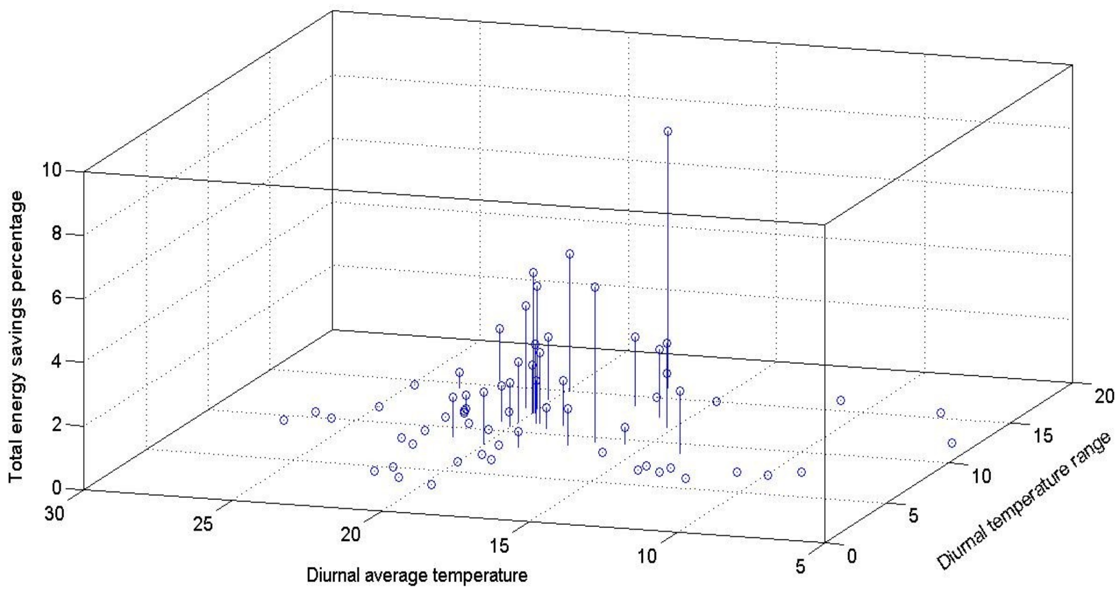


Figure 6-3: Total energy saving percentage verses diurnal outdoor average temperature and diurnal temperature range for investigated date.

6.1.2 Hourly outdoor air temperature

Figure 6-4 and Figure 6-5 show results for fan flow rates during the night between hour 7 (7 a.m.) and hour 3 (3 a.m.) versus outdoor temperature at that specific hour and temperature difference between indoor and outdoor. The results show that the minimum suitable temperature difference between outdoor and indoor to apply nighttime ventilation is 8 ˚C. Using the outdoor air with temperature difference less than 8 ˚C cannot reduce building energy consumption. Also, outdoor temperatures between 10 ˚C and 18 ˚C are appropriate for nighttime ventilation and energy savings of nighttime ventilation reduce significantly when the outdoor temperature is out of this range.

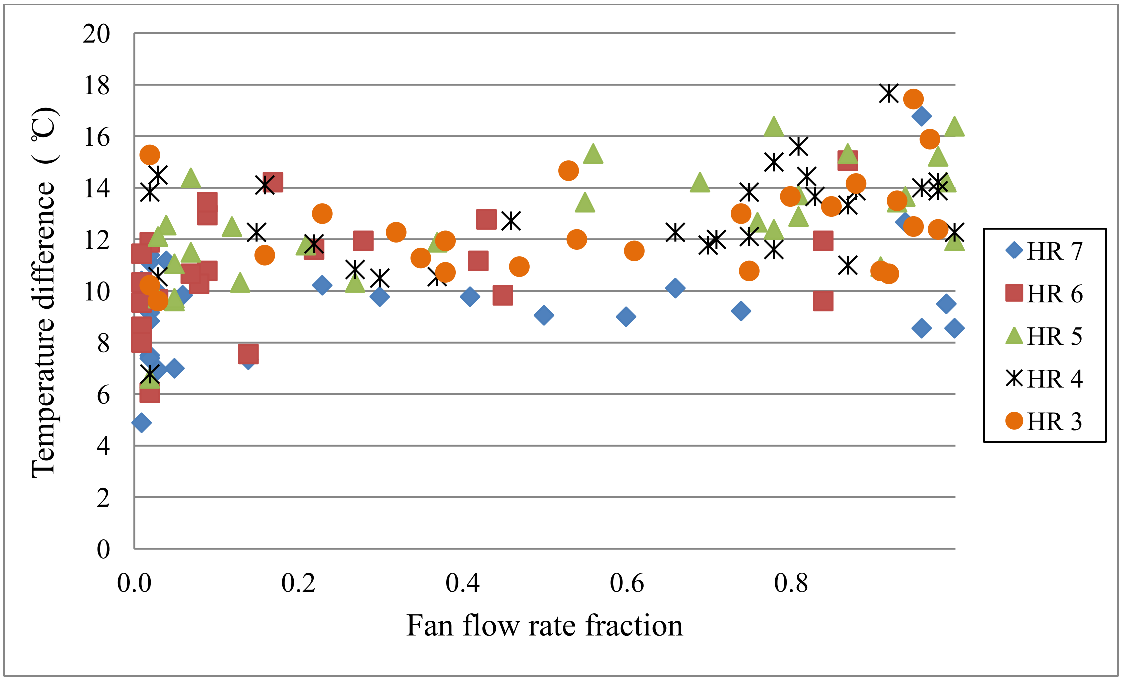


Figure 6-4: Nighttime fan flow rate fraction versus temperature difference between outdoor and indoor temperature for 5 hours before working hour during summer in Montreal

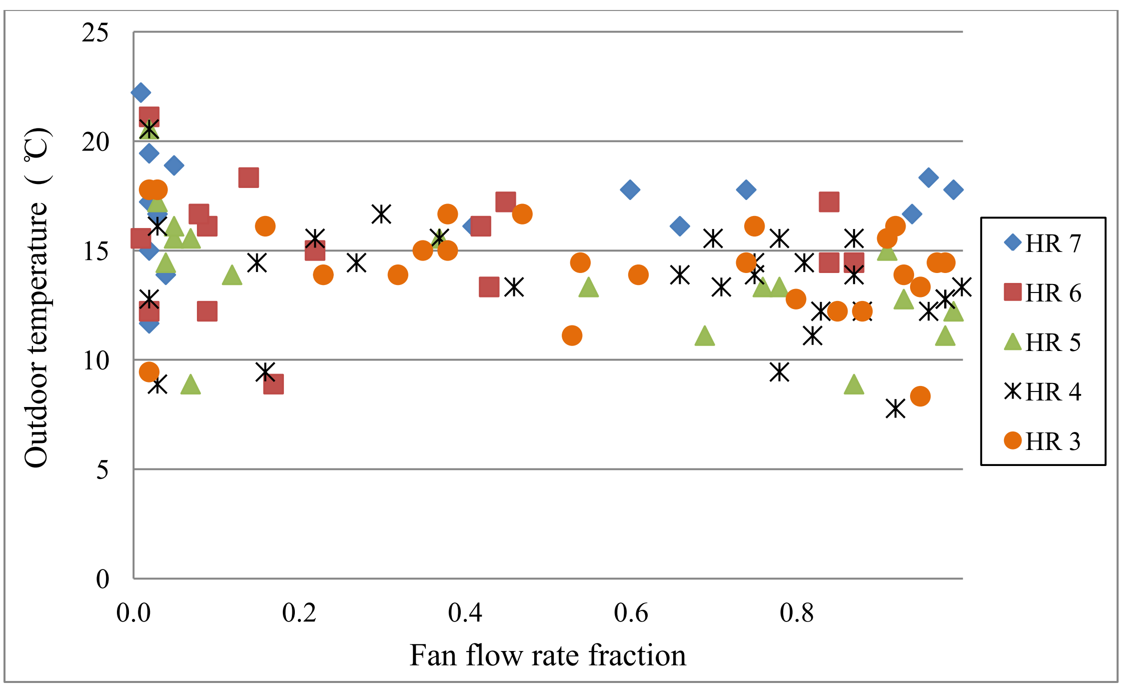
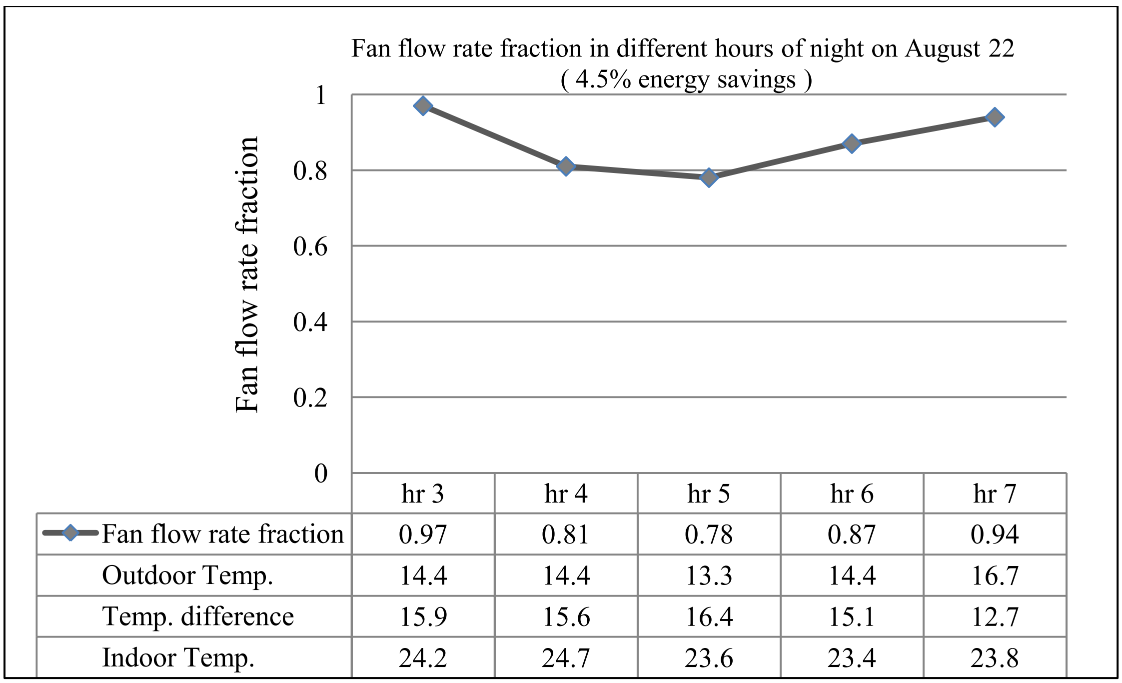


Figure 6-5: Nighttime fan flow rate fraction versus temperature difference between outdoor and indoor temperature for 5 hours before working hour during summer in Montreal

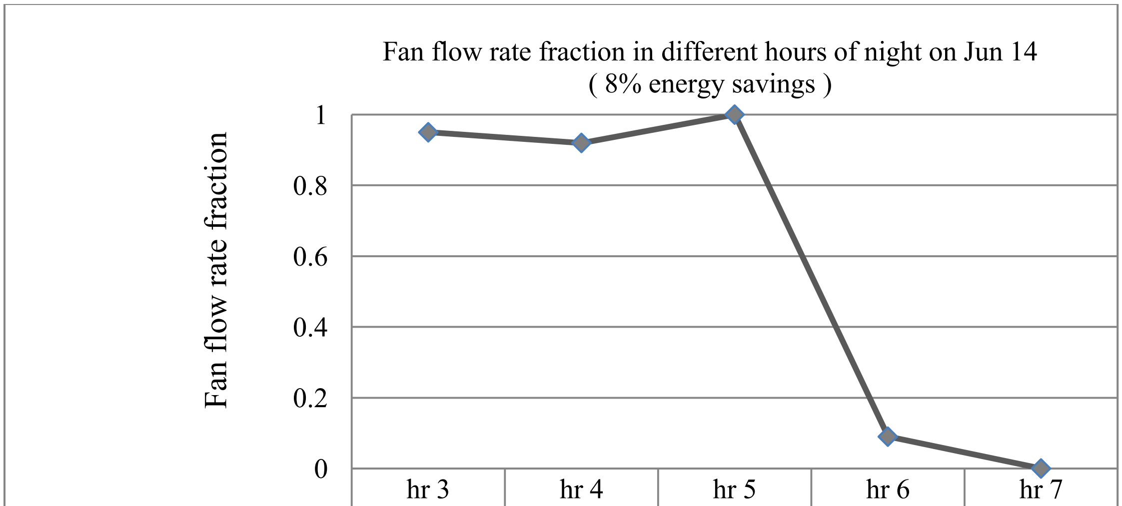
6.1.3 Results of hourly fan flow rates

To better understand the nighttime ventilation optimization, the hourly results for fan flow rates for some days with higher energy savings potential are shown in Figure 6-6, Figure 6-7, and Figure 6-8. The results show that optimization is converging towards an indoor temperature of about 23 ˚C at the beginning of the day. To reach this goal, optimization uses higher fan flow rates during hours with lower outdoor air temperatures and higher temperature differences between outdoor and indoor.



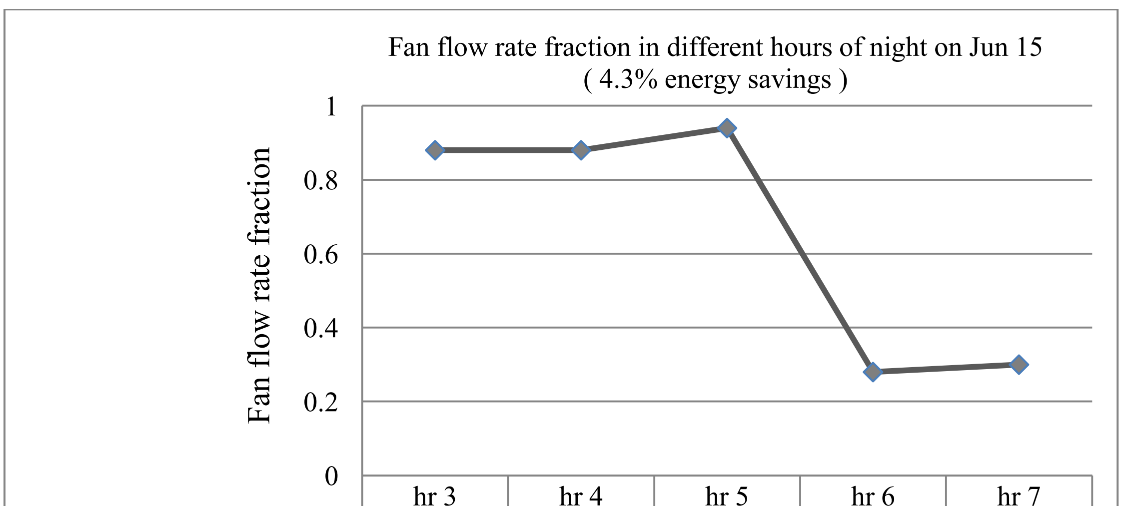
	hr 3	hr 4	hr 5	hr 6	hr 7
Fan flow rate fraction	0.97	0.81	0.78	0.87	0.94
Outdoor Temp.	14.4	14.4	13.3	14.4	16.7
Temp. difference	15.9	15.6	16.4	15.1	12.7
Indoor Temp.	24.2	24.7	23.6	23.4	23.8

Figure 6-6: Hourly fan flow rate fraction and temperatures from 3am to 7am for August 22 in Montreal



	hr 3	hr 4	hr 5	hr 6	hr 7
Fan flow rate fraction	0.95	0.92	1	0.09	0
Outdoor Temp.	8.3	7.8	8.9	11.7	14.4
Temp. difference	17.4	17.7	16.4	13.4	10.7
Indoor Temp.	20.2	19.4	18.8	21.9	22.9

Figure 6-7: Hourly fan flow rate fraction and temperatures from 3am to 7am for Jun 14 in Montreal



	hr 3	hr 4	hr 5	hr 6	hr 7
Fan flow rate fraction	0.88	0.88	0.94	0.28	0.3
Outdoor Temp.	12.2	12.2	12.2	13.9	16.1
Temp. difference	14.2	13.9	13.7	11.9	9.8
Indoor Temp.	22.3	21.7	20.9	22.8	23.4

Figure 6-8: Hourly fan flow rate fraction and temperatures from 3am to 7am for Jun 15 in Montreal

6.2 Integrating MATLAB with DOE-2 (application for shading position optimization)

A building energy use and cost analysis tool (DOE-2.1E) was used for building simulation and integrated with MATLAB for accurate building energy optimization. Results of shade position optimization are discussed in this section.

6.2.1 Effects of shading coefficients

Shading of the windows has three different effects on windows coefficients, these coefficients are: 1) radiation heat transmission, 2) illuminance transmission, and 3) conduction heat transfer. Three different types of shading are studied based on their effects on these coefficients. Thin shade reduces radiation, illuminance and conduction coefficients when it is completely closed to 25%, 20% and 65% of completely open shade coefficients, respectively.

Normal shade reduces radiation, illuminance and conduction coefficient when it is completely closed to 15%, 10% and 55% of completely open shade coefficients, respectively. Thick shade reduces radiation, illuminance and conduction coefficient when it is completely closed to 0%, 0% and 45% of completely open shade coefficients, respectively. The optimization results (Table 6-2) show that on very cold and hot days shades stay closed since the effect of heat conduction is more important than the effect of solar heat gain and illuminance transmission from windows. Also, on very hot days closing shades reduces solar heat gain through windows (decreasing cooling energy consumption). During transient seasons with mild temperature during the day, optimization of shading position becomes more effective. In these seasons optimization can find the correct combination of shade position for different zones to benefit from both heat gains and lighting without unnecessary increase of heating and cooling energy consumption of zones.

Table 6-2: Optimized shade position of different zones in different date

Date D/M/H	Outdoor Temp.	Horizontal solar radiation w/m^2	Shade position of zone 1	Shade position of zone 2	Shade position of zone 3	Shade position of zone 4
10 Jan 09	-12	50	0.94	0.85	0.92	0.86
10 Feb 09	2.8	91	0.1	0	1	0.9
10 Feb 17	0.5	19	1	1	0.93	0.93
10 Mar 09	-10	343	0	0	0.7	0.92
10 Mar 17	-7	227	0.4	0	0.4	0.3
21 Mar 11	-3	753.5	0	0	0	0
12 Apr 09	4.5	646	0	0	0	0
12 May 09	19.5	441	0.9	0.95	1	0.86
21 Jun 13	22	892	1	0.9	0.95	1
15 Jul 11	26	883	1	0.9	0.95	0.85
15 Jul 14	27	751	0.98	1	1	0.97
21 Jul 11	26	451	0.9	0.95	0.95	0.8
18 Aug 09	65	185	0.95	0.9	0.6	0
13 Sep 16	23	375	1	0.9	0.95	1
14 Sep 09	15.5	41	0.1	0	0.2	0
14 Sep 16	16	101	0.5	0.8	0.3	0.6
12 Oct 14	14	378	1	0.95	0.95	1
14 Oct 09	15.5	70	0.15	0.65	0.3	0.1
19 Nov 09	-7	205	0.7	0.8	0.8	0.8
21 Nov 13	0.5	145	0.9	0.9	0.9	0.7
26 Dec 09	-3	35	0.95	0.9	0.9	0.8

It is possible to see that shade positions are different in different zones based on solar heat gain and illuminance at each zone orientation. On hot days optimization keeps the shade open up to position that the reference point illuminance is satisfied; at the same time it reduces solar heat gain to decrease building cooling energy consumption. Figure 6-9 shows building energy consumption on a sample day in transient seasons for completely closed and open shades, compared to optimized shade position. Results show that using thick shades gives optimization more flexibility for energy savings compared to thin shades.

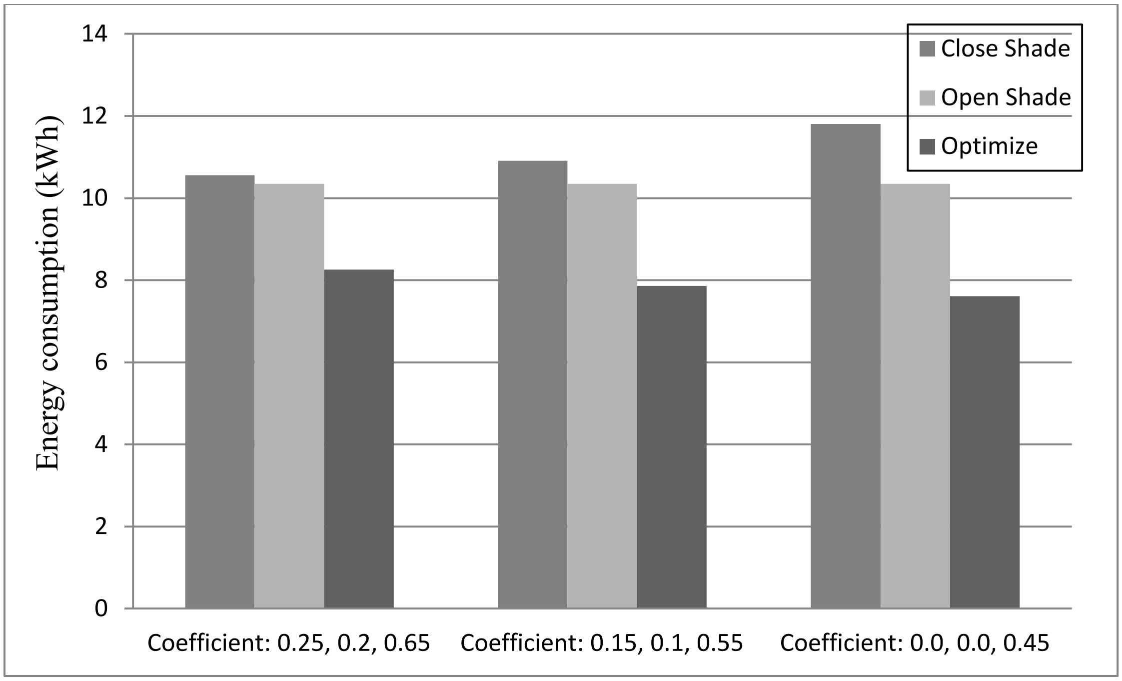


Figure 6-9: Building energy consumption in sample day for completely close and open shade compare to optimized shade position

6.2.2 Artificial light energy consumption

Three different artificial lighting energy consumptions are investigated. These energy consumptions are 5.4, 10.7, and 16 w/m^2. Results show that building energy consumption increases with rising artificial lighting energy consumption as we expected (Figure 6-10). Comparing the percentage of energy savings between optimized and open shade cases show that lower artificial lighting energy consumption has a higher potential for energy savings (25%) compared to higher artificial lighting energy consumption (20%). The energy savings potential of lower artificial lighting energy consumption becomes more important in cooling seasons when solar heat gain has a detrimental effect on building energy consumption. Lower artificial lighting energy consumption helps optimization to keep shades closed as much as possible during summer in order to reduce solar heat gain without significant increase in light energy consumption.

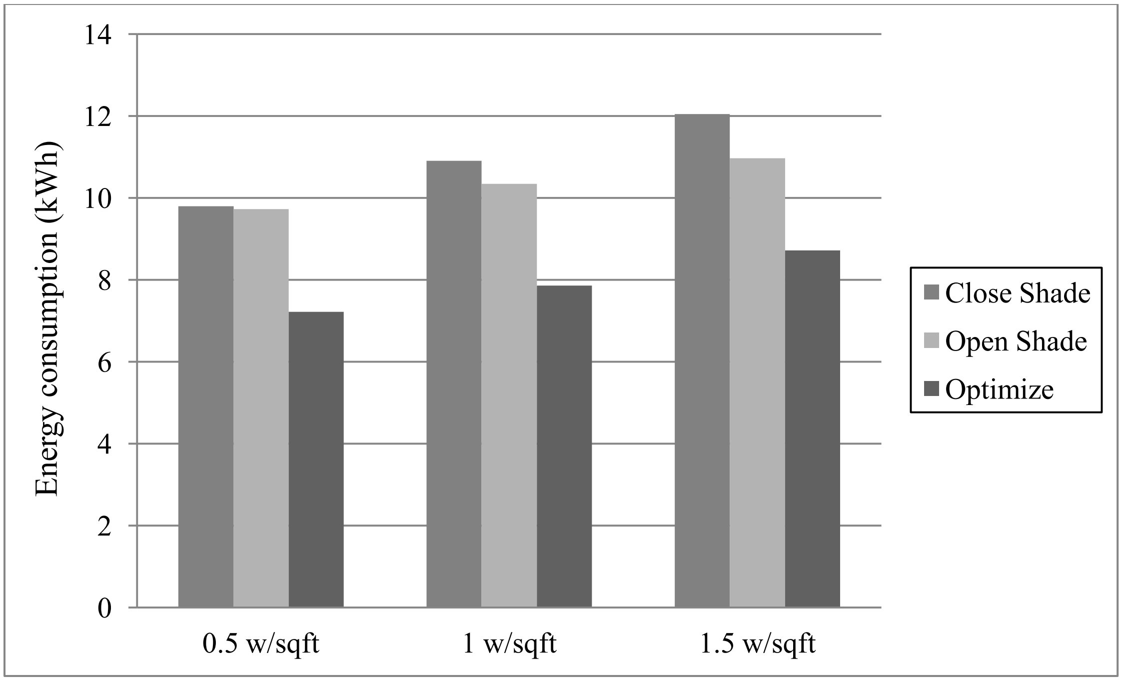


Figure 6-10: Building energy consumption for different artificial lighting energy consumption

6.2.3 Zones illuminance set-point

Illuminance set-points of 25, 50, and 100 foot-candles for each zone are investigated. Results of building energy consumption and optimized energy savings are shown in Figure 6-11 for these set-points. Increasing the indoor illuminance set-point increases closed-shades building energy consumption as it expected, since zones require more lighting energy to satisfy higher illuminance set-points. Also lower set-points have higher energy savings potential, since shading optimization have more flexibility to use daylighting to achieve the illuminance set-point while keeping shade at a lower position to prevent unnecessary heat gains from windows.

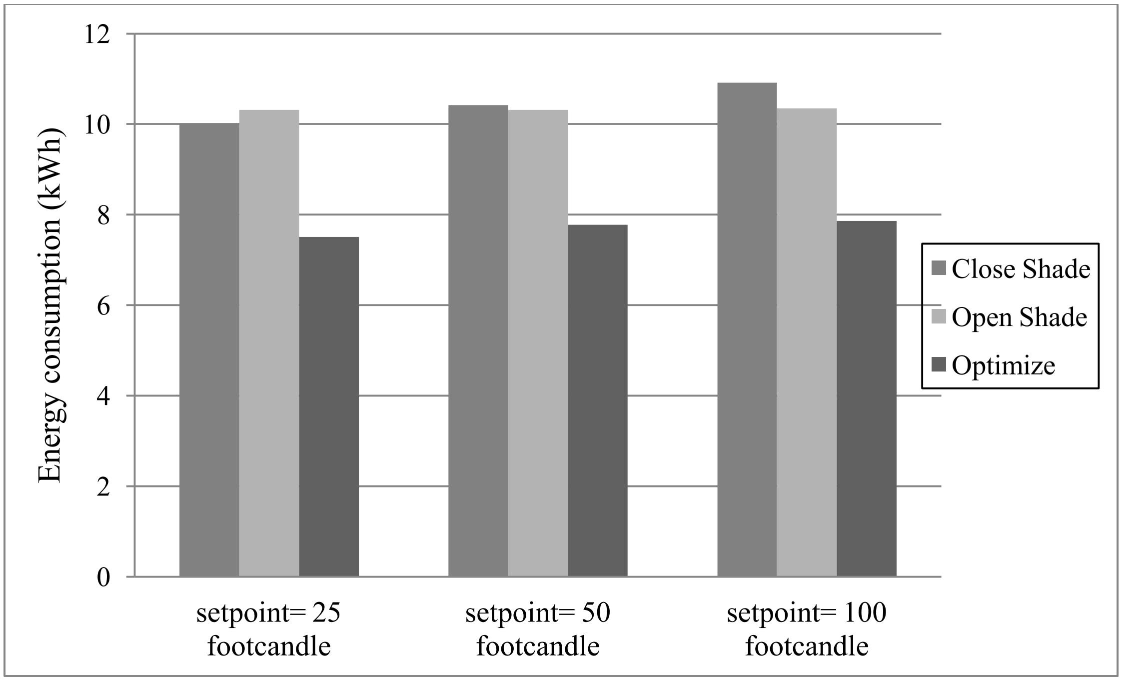


Figure 6-11: Building energy consumption for different illuminance set-point

6.3 Methods of increasing speed and accuracy of optimization (stochastic search coupling with local search)

Pattern search (PS) is a family of numerical optimization methods that do not require the gradient of the equations for solving the optimization problem. Hence PS can be used on functions that are not continuous or differentiable and when the exact equations for objective function calculation are not available.

See references [119, 120] for more detailed descriptions of the PS algorithms and their convergence analysis. For more detailed investigation of pattern search optimization, PS results are compared with nonlinear (exact) optimization results for the RC-network model.

The results show that by using starting point far from optimal results PS could get trapped on the local minimum and reach results different than optimal results. For solving this problem the PS needs to be rerun with different starting points or introduced by starting point near global minimum. Figure 6-12 shows the energy optimization results of a sample RC-network model of the building. The results of the nonlinear optimization and PS method with random starting point (base) and starting point with deviation 10% and 20% (0.9 N and 0.8 N) from nonlinear optimization results are shown in this figure.

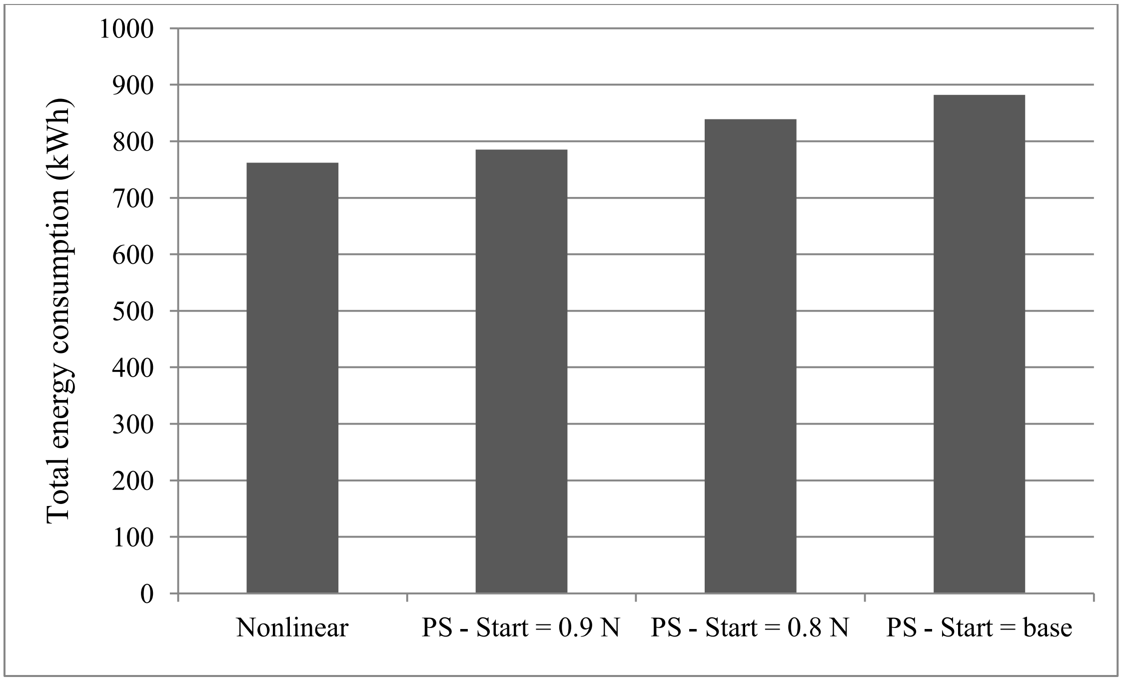


Figure 6-12: Investigation of pattern search method by comparing different start point in respect to nonlinear optimization results for 5 zones

Since the genetic algorithm searches the specific domain randomly it is time consuming for big domain optimization. It is possible to stop GA after a finite number of iterations and easily combine the GA with the Pattern Search (PS) algorithm to produce a hybrid algorithm that uses the GA for the global search and uses the PS for the local search. Thus, the global exploration of the GA reduces the risk of getting attracted by a local minimum which is not global, and the PS enables clear convergence statements in domains where the cost function is smooth. Figure 6-13 shows the results of energy optimization of one zone by using GA and combination of GA and PS. The results show GA optimization with limited number of iterations is not accurate enough and using a multi-start GA increases the accuracy while making the optimization very time consuming. Combining global optimization with local optimization is possible by applying local search to the results of GA for faster and more precise optimization.

The combination of GA and PS finds better control parameters and saves more energy. In addition, it is faster than GA since this optimization requires less iteration in the GA part, which increases the speed of optimization significantly.

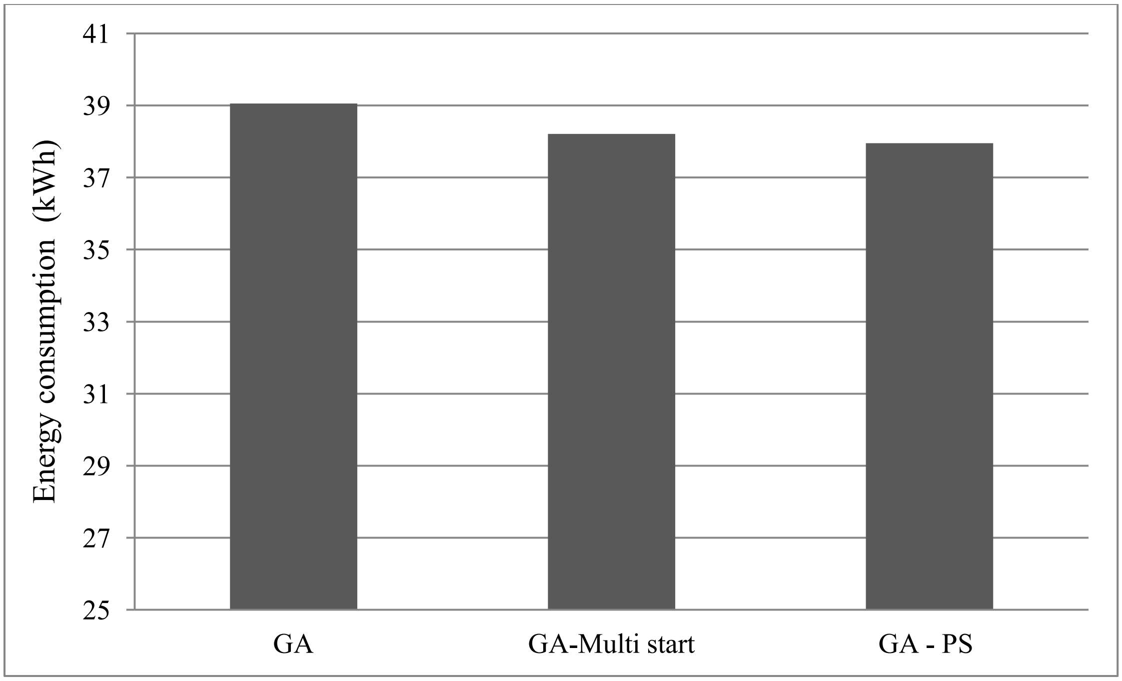


Figure 6-13: Comparison of different GA optimization methods and combination of GA and PS (Pattern Search) method for one zone

Figure 6-14 shows the results for energy consumption of one zone with different optimization methods compared to the scheduled basecase. The results show that the combination of GA and PS saves more energy and optimizes faster. Also in most cases applying PS only on shade position as a most effective parameter is enough for precise building energy optimization.

Figure 6-15 shows energy savings percentage and optimization time for genetic algorithm and combination of genetic algorithm and pattern search method with different iteration number. The combination of genetic algorithm and pattern search optimization leads to higher energy savings with similar optimization time compare to genetic algorithm. Using hybrid optimization method increases building energy savings by 10% to 20%. The hybrid optimization method can be used to reach similar energy savings in less time when the fast optimization becomes the priority in real time control.

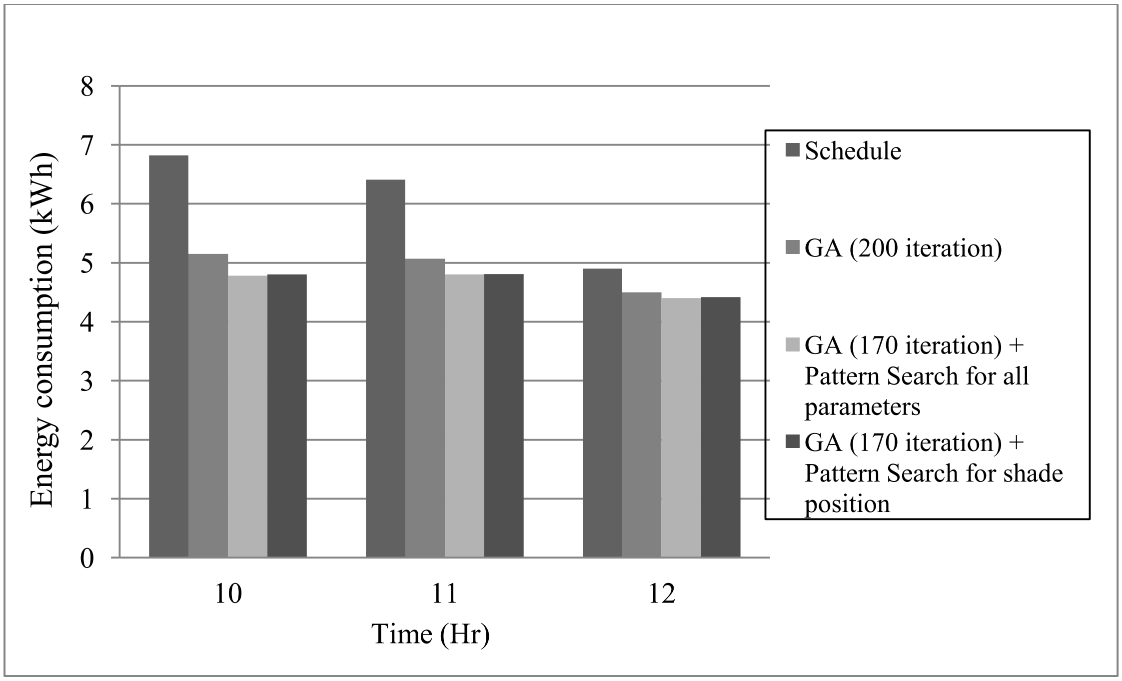


Figure 6-14: Results for energy consumption of one zone with different optimization methods compare to scheduled basecase for May 3, hours 10 to 12 (GA: Genetic Algorithm, PS: Pattern Search)

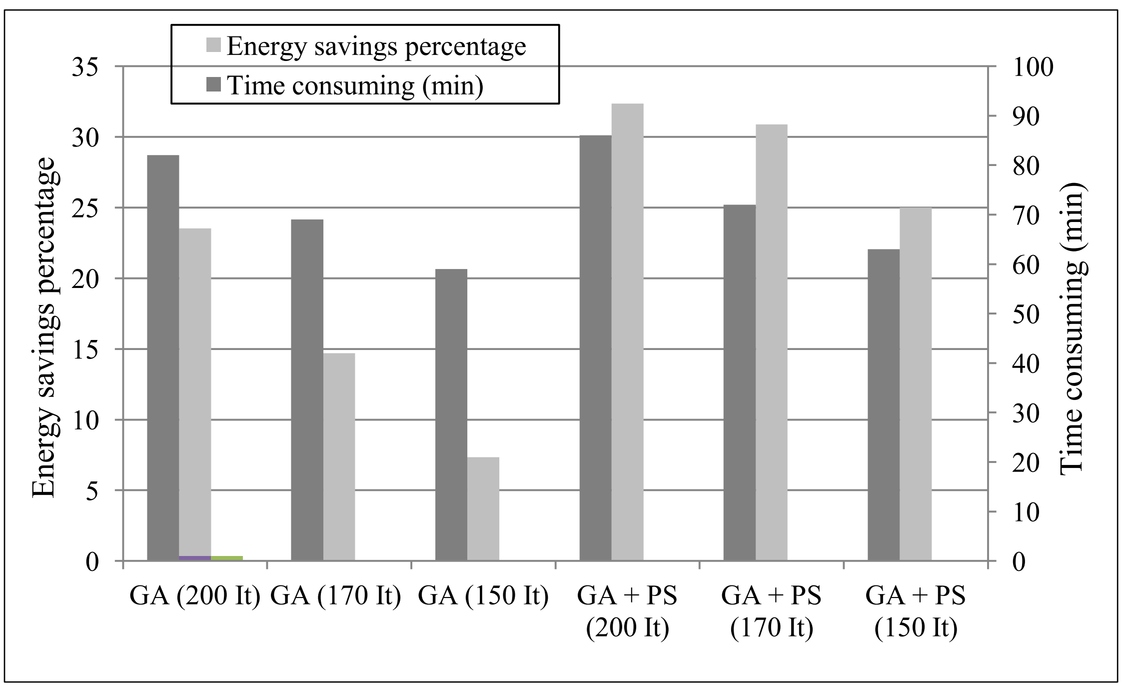


Figure 6-15: Results of energy savings percentage and optimization time for one zone with different optimization methods and iteration number compare to scheduled basecase for May 3, hours 10 (GA: Genetic Algorithm, PS: Pattern Search)

6.4 Methods of increasing speed and accuracy of optimization (Rule-base decision making coupled with stochastic search)

Several methods are available for solving an optimization problem such as: constraint based algorithms, which try to find out the relation between the variables and optimization objectives in order to extract the algorithm for finding an optimized result; search and scoring based algorithms, which search in a variables domain, looking for set of variables that obtain the best optimized results, based on objective function for scoring. In this section, rule-base decision making as an example of constraint method is compared with genetic algorithm as an example of search method. Also these two methods are combined to take advantage of each one for fast and accurate optimization.

The results in Figure 6-16 and Table 6-3 show that applying simple rules (four rules between three variables) can reduce building energy consumption. Having better savings requires modified and more complex rules based on optimization results. Optimization based on the genetic algorithm reduces energy consumption more than rule-base while it requires significant time for optimization. Combining the rule-base and the genetic algorithm increases speed and accuracy of optimization by reducing optimization variables and domain. in this method rule-base decision making runs before GA to make decisions for some of the variable amounts or modifing the search domian for them. Rule-base algorithm makes decision about shade position, indoor temperature, and fresh air fan flow rate based on outdoor air temperature and solar radiation. Decision about exact value of these parameters or their acceptable range decreases optimization domain that leads to faster optimization.

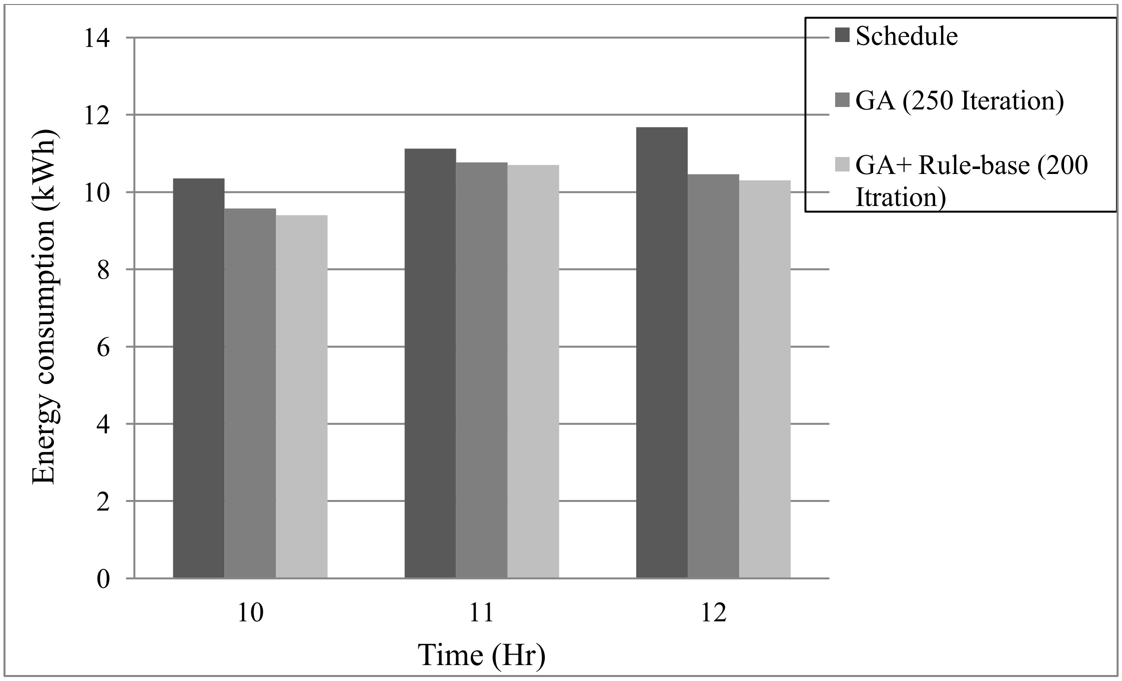


Figure 6-16: Energy consumption on one zone for GA and combination of GA + Rule-base for August 18, hours 10 to 12

Table 6-3: Comparison of genetic algorithm optimization and Rule-base (Rb) combined with genetic algorithm (GA)

Date	Method	Cooling kWh	Heat Rej kWh	Ventilation kWh	Total	Speed of optimization (min)
11-Aug	Base	87.8	17.2	26.8	136.9	1
	GA	77.9	16.3	33.8	133.1	82
	Rb-GA	76.5	16.2	34.7	132.5	63
12-Aug	Base	83.6	17.4	23.1	129.2	1
	GA	76.1	17.2	30.1	128.6	79
	Rb-GA	73.8	16.6	31.3	126.8	61
18-Aug	Base	58.3	14.2	17.6	95.0	1
	GA	54.4	13.5	21.7	94.5	77
	Rb-GA	55.0	13.6	20.4	94.0	56
19-Aug	Base	86.4	17.2	29.1	137.9	1
	GA	84.7	16.4	30.7	137.0	82
	Rb-GA	83.5	16.6	31.0	136.4	59

6.5 Effect of optimization parameters on optimization speed and energy savings

Effects of number of iterations and number future-hours variables on multi-hour optimization results with GA are investigated in this section. In this case for the current hour all of the control variables are optimized while some of them are chosen for optimization for future-hours and the rest are assumed equal to the current hour amount. Results show that the number of variables has significant effect and should be chosen correctly for multi-hour optimization. Optimization with a huge number of variables reduces the speed of optimization and also increases the chance of divergence or incorrect results with constant number of iterations. Using very small number of variables reduces the potential of energy savings. The other effective parameter on optimization results is the number of iteration. A higher number of iterations increases accuracy of final results for reaching to optimal answer; on the other hand it decreases optimization speed significantly. As a result, finding the correct balance for the number of iterations and variables is very important. Figure 6-17 and Figure 6-18 show the building energy consumption results of GA for different numbers of iterations in current hour optimization. The results show that by increasing number of iteration accuracy of optimization increase while the optimization speed decreases.

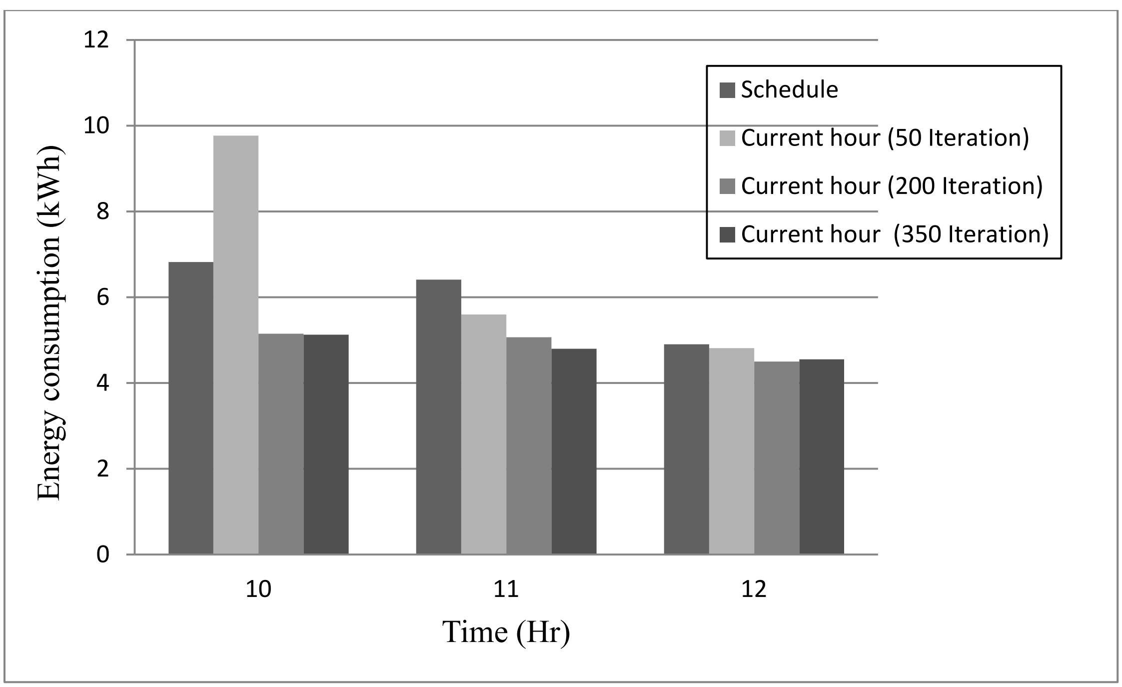


Figure 6-17: Building energy consumption results of GA for different number of iteration in current hour optimization for May 3, hours 10 to 12

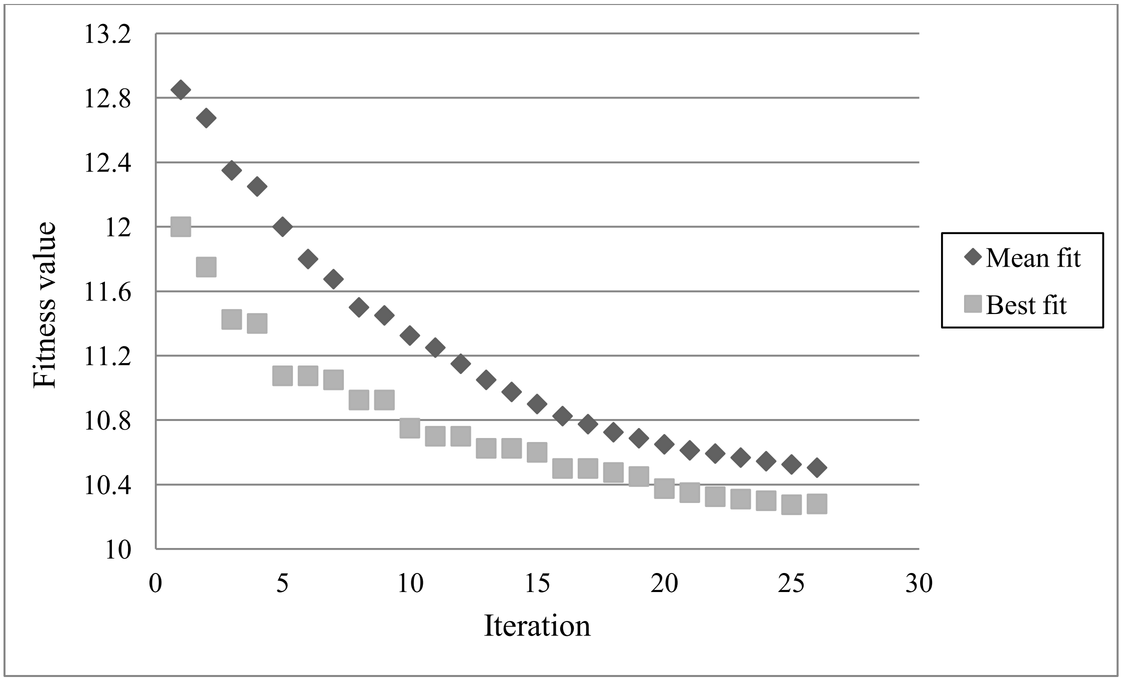


Figure 6-18: Best fitness value and mean fitness value of objective function based on number of iteration for genetic algorithm optimization

Figure 6-19 and Figure 6-20 compares the effect of iteration number and number of variables in multi-hour optimization. There is an optimal combination of iteration and number of variables that can satisfy required accuracy and energy savings while keeping the time consumption of optimization in an acceptable range. The results show that increasing number of considered variables from 10 to 18 increases optimization time significantly. Also, higher number of variables requires more iteration to reach optimal results.

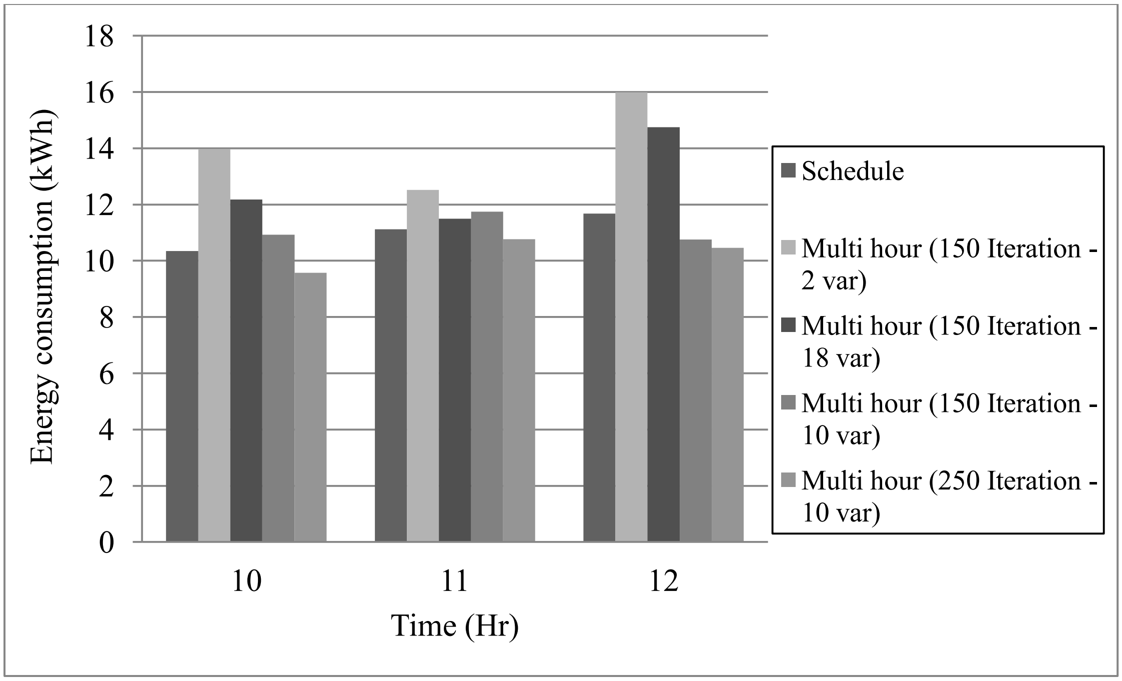


Figure 6-19: Energy consumption results of multi hour optimization whit different number of iteration and variables for August 18, hours 10 to 12

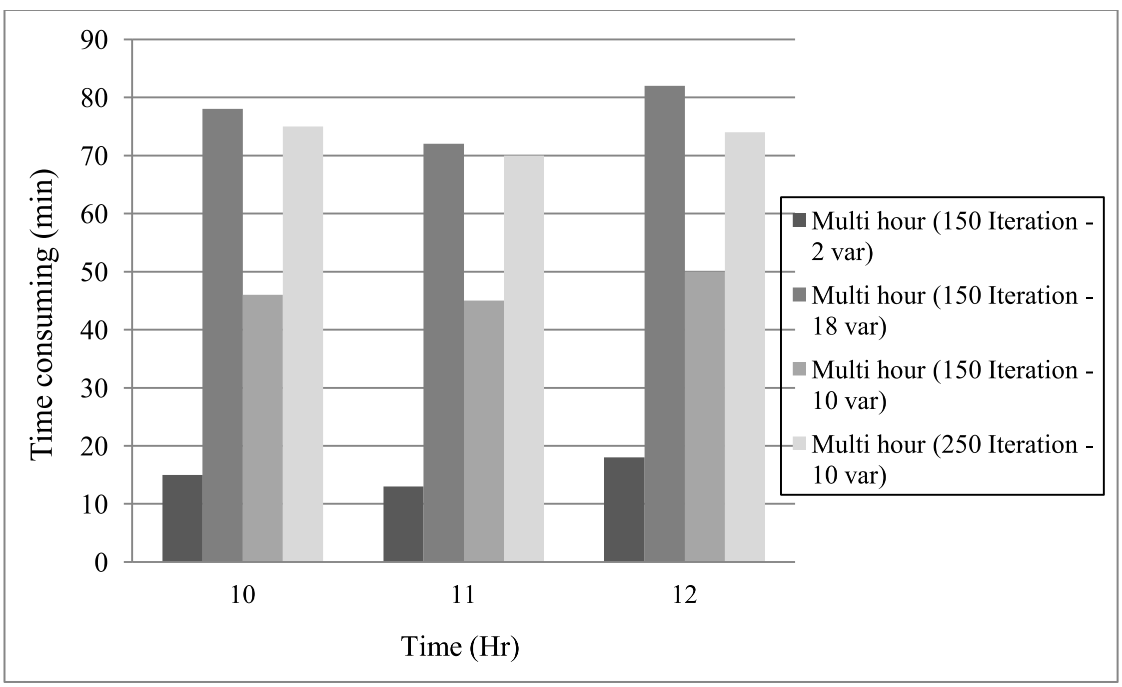


Figure 6-20**:** Time consumption results of direct multi hour optimization whit different number of iteration and variables for August 18, hours 10 to 12

The method of calculating the objective function is another important parameter in speed of optimization. As it is discussed in previous chapters, the direct and the indirect methods for calculating the objective function are introduced. In the direct method the objective function is calculated by the DOE-2 and in the indirect method it is calculated by trained neural network. Figure 6-21 compares the energy consumption of direct and indirect method. The results show energy calculation difference less than 1.5% between these two methods. By comparing the energy calculation results of rerunning one of these methods for specific hour, the results show similar difference between the energy calculations that is came from the optimization with stochastic method (Figure 6-22). Comparing the optimization computational time of the direct and the indirect optimizations show significant difference between them. The indirect method required more time for first iterations since it needs initial time for training neural network. However, computational time does not increase considerably by increasing the number of iterations. While, the direct method computational time increases significantly by increasing the number of iterations (Figure 6-23).

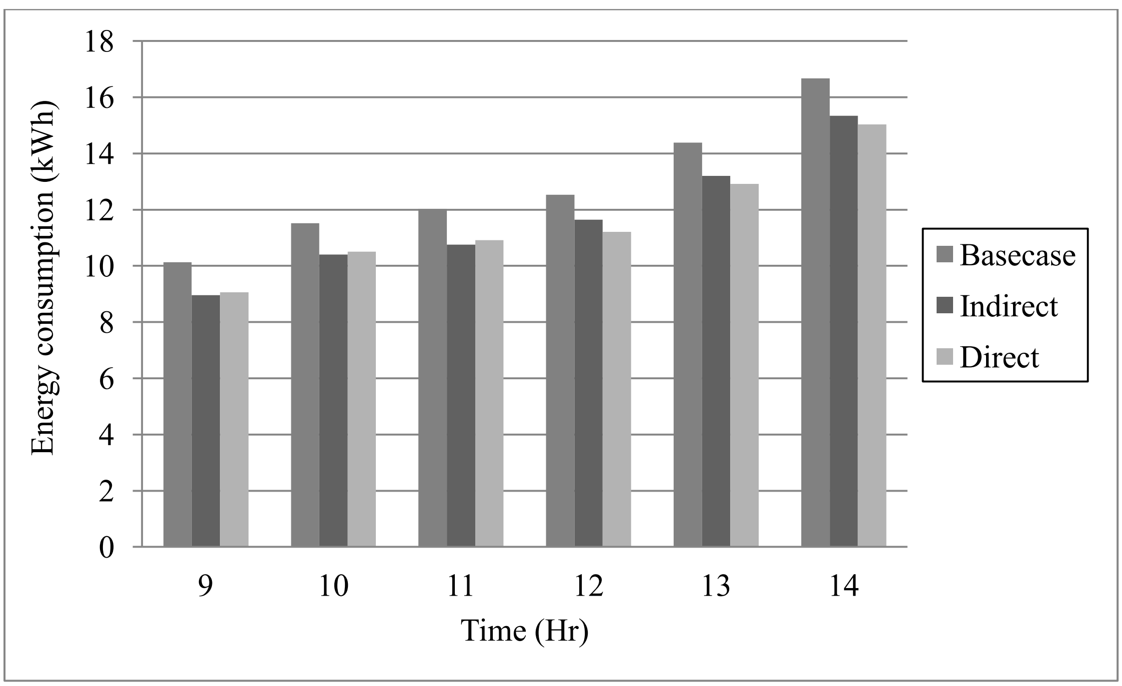


Figure 6-21: Energy consumption results of direct and indirect method for calculating of objective function for Aug 18, hours 9 to 14

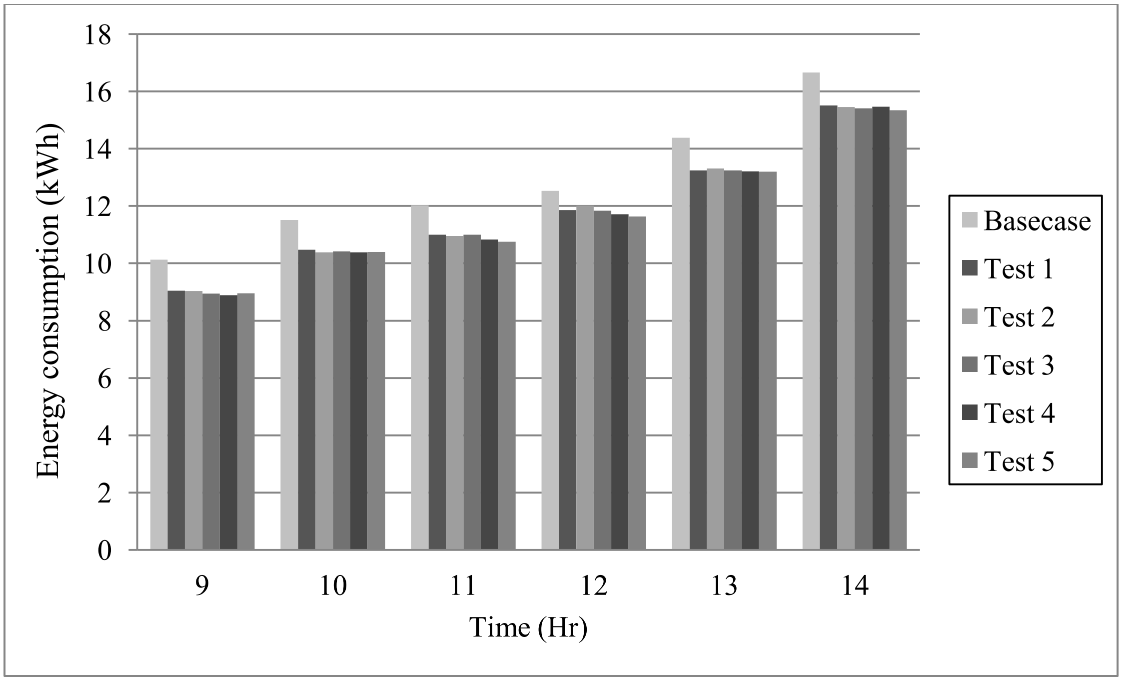


Figure 6-22: Energy consumption results of rerunning indirect method for calculating of objective function for Aug 18, hours 9 to 14

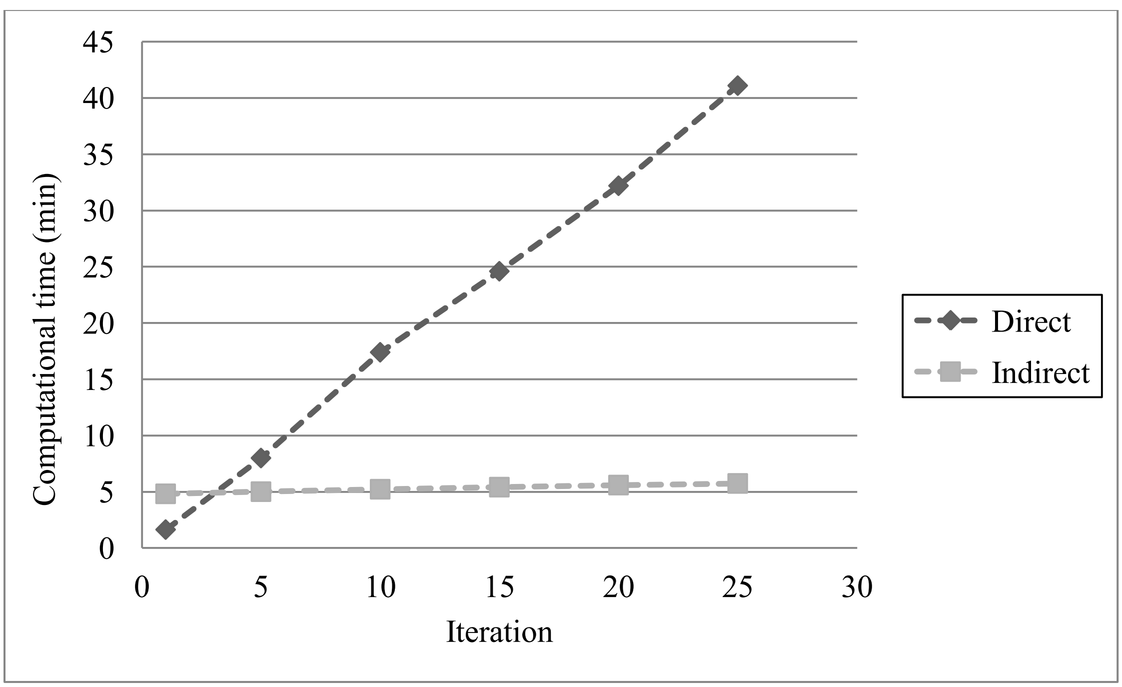


Figure 6-23: Computational time of the direct and indirect methods for objective function calculation versus number of iterations

6.5.1 Comparison between energy and cost objective functions

Two objective functions could be defined for optimizations: energy consumption and cost. Based on the importance of each of these objectives, one of them can be chosen. The results for control parameters and savings can be different when using each of these objectives.

For investigation of the effects and differences of these objectives a sample hour is optimized based on each of them. The difference between these two objectives could be more important in multi-hours optimization.

The results for sample hour optimization of shade position with objective functions of cost and energy are shown in Figure 6-24 and Figure 6-25. The results show different optimized shade position based on objective function that leads to different cost and energy consumption.

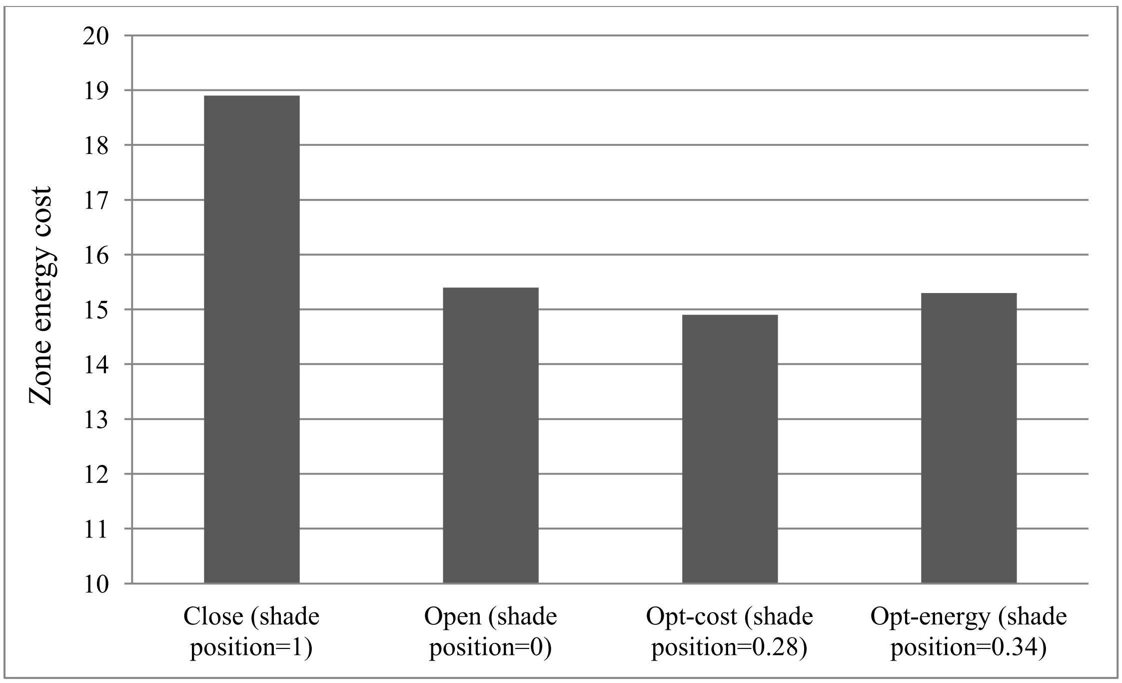


Figure 6-24: Zone energy cost of close, open, and optimized position based on cost and energy objective functions for September 12, hour 13

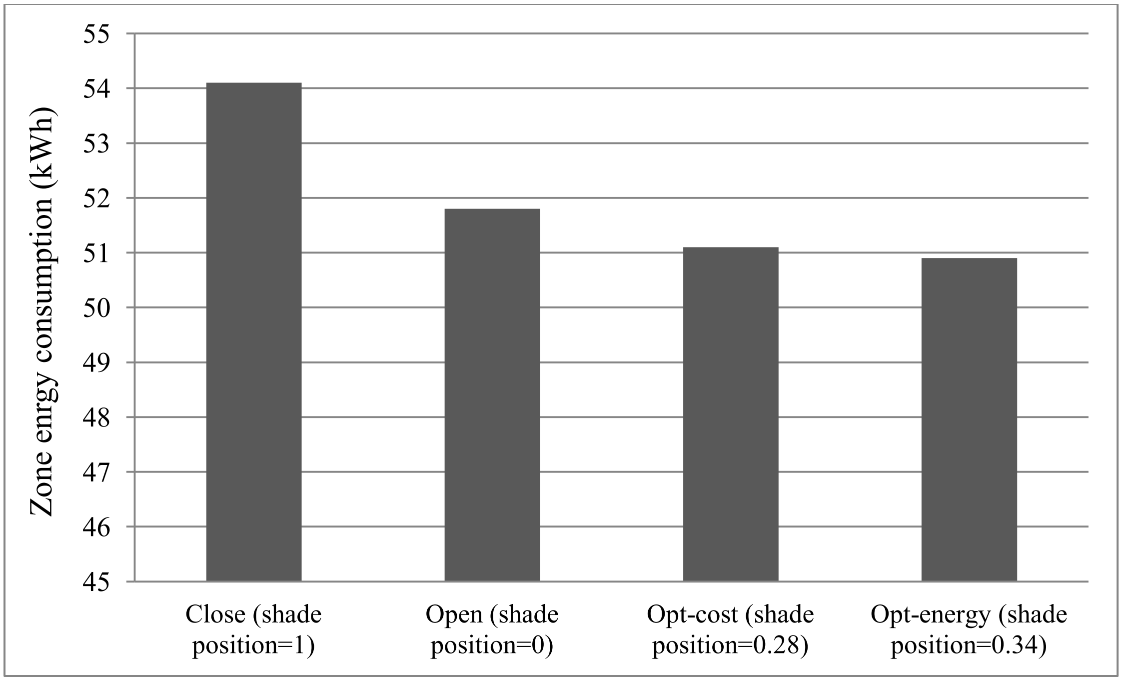


Figure 6-25: Zone energy consumption of close, open, and optimized position based on cost and energy objective functions for September 12 hour 13

6.6 Building integrated optimization

In previous sections, effective parameters, optimization methods, methods of increasing speed of optimization, and different objective functions are investigated. Based on the results of these investigations an integrated optimization tool is developed for multi-hour optimization of a whole building with cost and energy objective functions. This integrated optimization tool includes:

- Rule-based decision making
- Genetic algorithm global optimization
- DOE-2 for building energy and cost calculation
- Neural network for building energy consumption prediction
- Local search for more accurate final results

Rules of decision making are developed in two categories: first, simple rules that can be developed based on general knowledge about building energy consumption; and second, more complicated rules that should be extracted from optimization results. These rules are applied in decision making algorithm before the genetic algorithm optimization to decrease optimization domain and range of variables.

The genetic algorithm is used as the main optimization method for current hour or multi-hour optimization based on cost or energy objective functions. GA can be connected directly with DOE-2 for energy and cost objective function calculation or indirectly with a neural network that is trained with DOE-2 results.

After optimization with GA, its results are used as an initial value for local search to improve the optimization results. Figure 6-26 shows the complete process of integrated optimization.

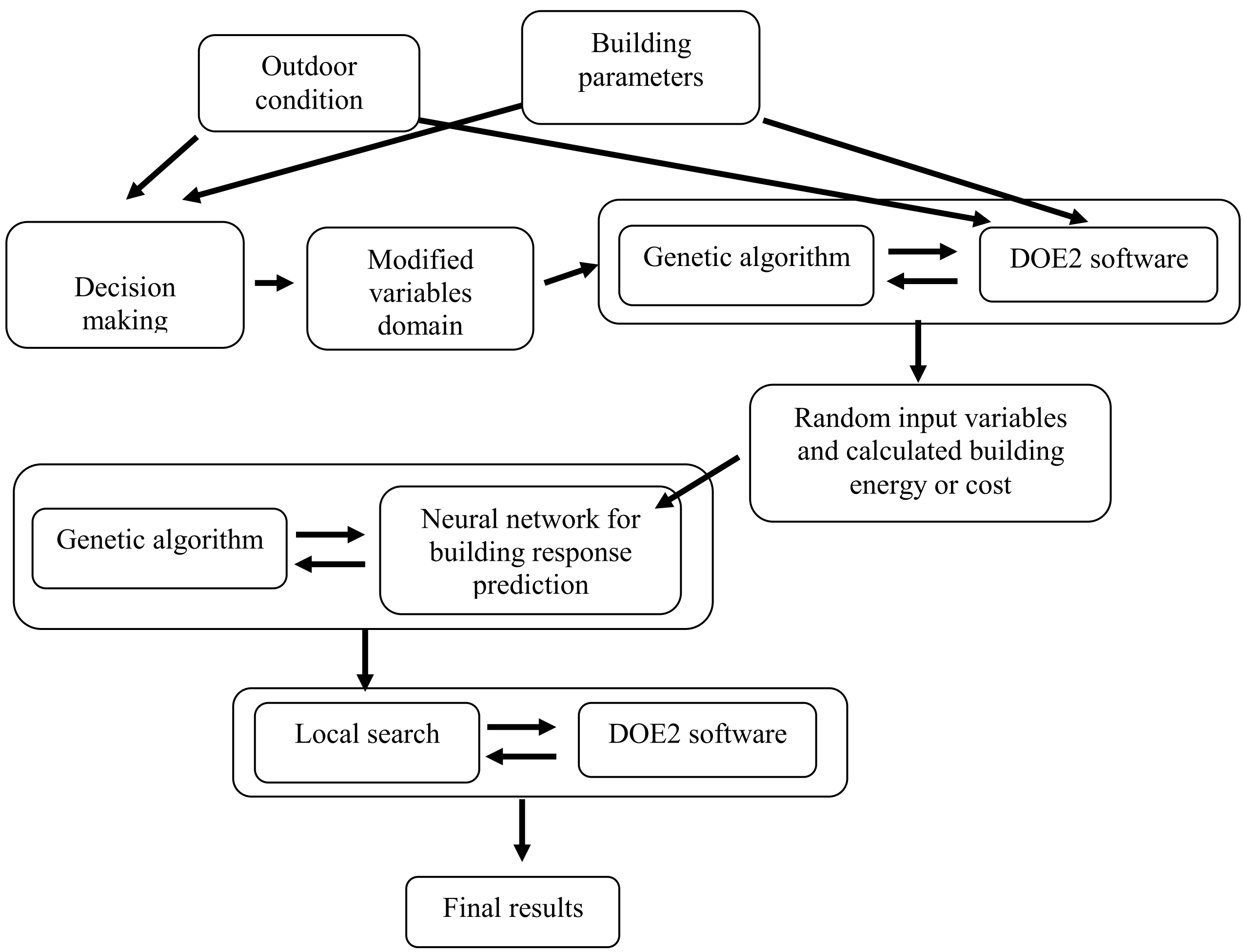


Figure 6-26: Integrated building optimization process

Figure 6-27 shows average building total energy savings in different months. The results show energy savings between 10% and 30%; also higher energy savings potential could be expected during transient seasons compared to very hot or very cold seasons. Sources of energy savings come from various strategies; using solar outdoor illuminance from the windows to reduce indoor lighting energy consumption; using solar heat gain from the windows during the heating periods to reduce heating energy consumption; controlling temperature during the day for minimum energy consumption and storing cooling or heating energy; adjusting outdoor air flow rate for air quality and energy consumption management.

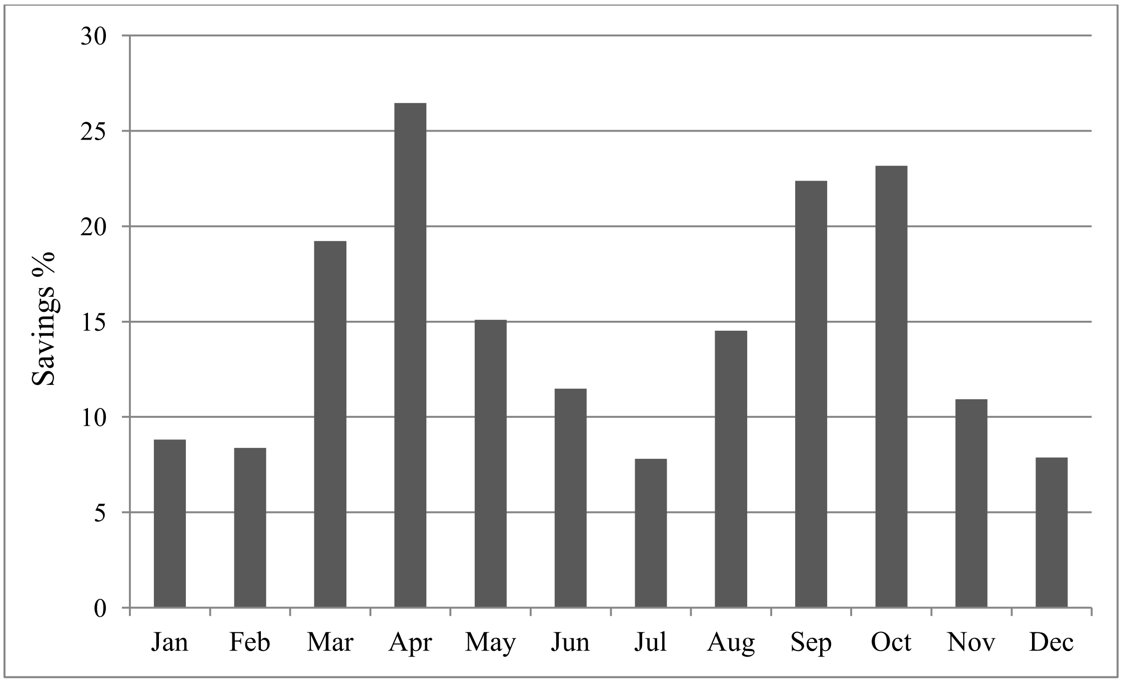


Figure 6-27: Building total energy savings for different months with current hour integrated optimization

All of these sources have more potential during transient seasons with mild outdoor temperature and solar radiation. For example, controlling shade positions for heat and illuminance gain from the windows is more flexible since heating and cooling conductions have less effect during these seasons; also during very cold or hot seasons it is necessary to keep indoor temperature at the extremums and there is no significant potential for energy savings for temperature control as there is in transient seasons; in addition, using outdoor air for energy management requires mild outdoor air temperature, otherwise bringing in outdoor air will increase building cooling or heating energy consumption.

Figure 6-28 shows the maximum energy savings potential of a day based on average outdoor temperature of working hours in that day. Changing the objective function from energy consumption to cost can affect percentage of savings. In the case of current hour optimization in a building with a complete electrical HVAC system the results of cost savings are similar to energy savings results. However, for a building with an HVAC system that works with gas and electricity, time-of-use price of electricity and its ratio to gas price can affect optimization results.

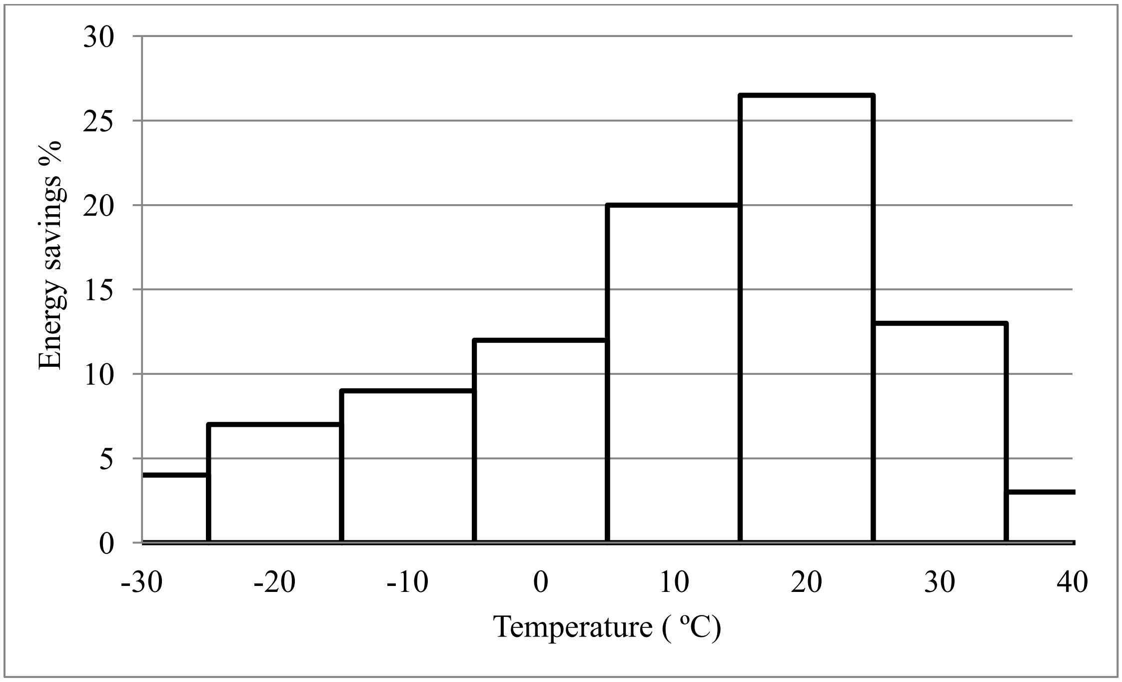


Figure 6-28: Maximum energy savings potential based on working hours daily average temperature

For example when it is peak hours with high electricity, cost optimization gives priority to reducing lighting power instead of heating energy consumption. In this case demand response and time-of-use price from the utility becomes more important. Figure 6-29 shows the results of cost savings based on time-of-use price compare to energy savings.

Reducing peak load is another advantage of integrated optimization. Using integrated optimization can reduce energy consumption at peak hours, which leads to lower building energy cost as well as the potential of reducing cooling and heating systems sizes. It also can help utilities during peak hours as a part of a demand response project. Table 6-4 shows results of peak load in each month and their savings by using integrated optimization.

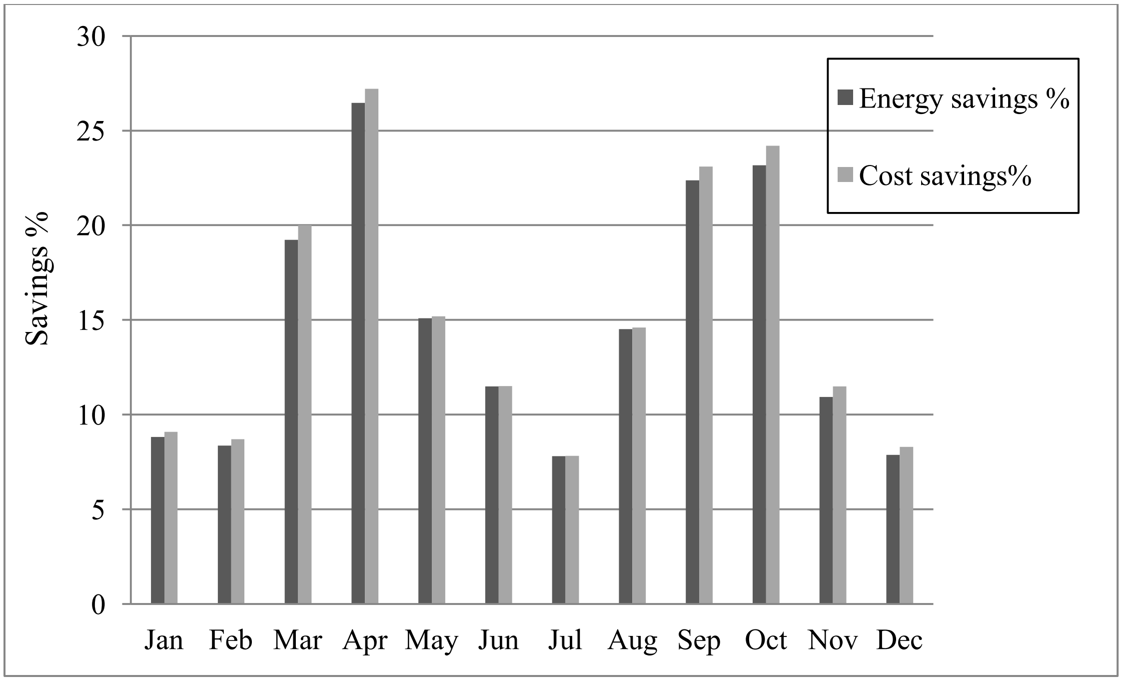


Figure 6-29: Cost savings based on time-of-use price compare to energy savings

Table 6-4: Monthly peak load and possible peak load savings by using integrated control

Month	Peak load (kW)	Savings %
Jan	219.64	32%
Feb	233.79	34%
Mar	165.4	42%
Apr	146.72	40%
May	74.98	36%
Jun	29	21%
Jul	34.2	23%
Aug	36.4	26%
Sep	35.09	31%
Oct	110.26	40%
Nov	173.99	43%
Dec	219.24	35%

The results show peak load savings from 21% to 43%. The effective parameters on these peak load savings are: (1) solar illuminance control to reduce lighting energy consumption by optimizing shade position, (2) solar heat gain and conduction heat transfer optimization by controlling shade position, (3) temperature control and using stored energy in building envelope, and (4) outdoor air flow rate control based on outdoor air temperature that can reduce building energy consumption.

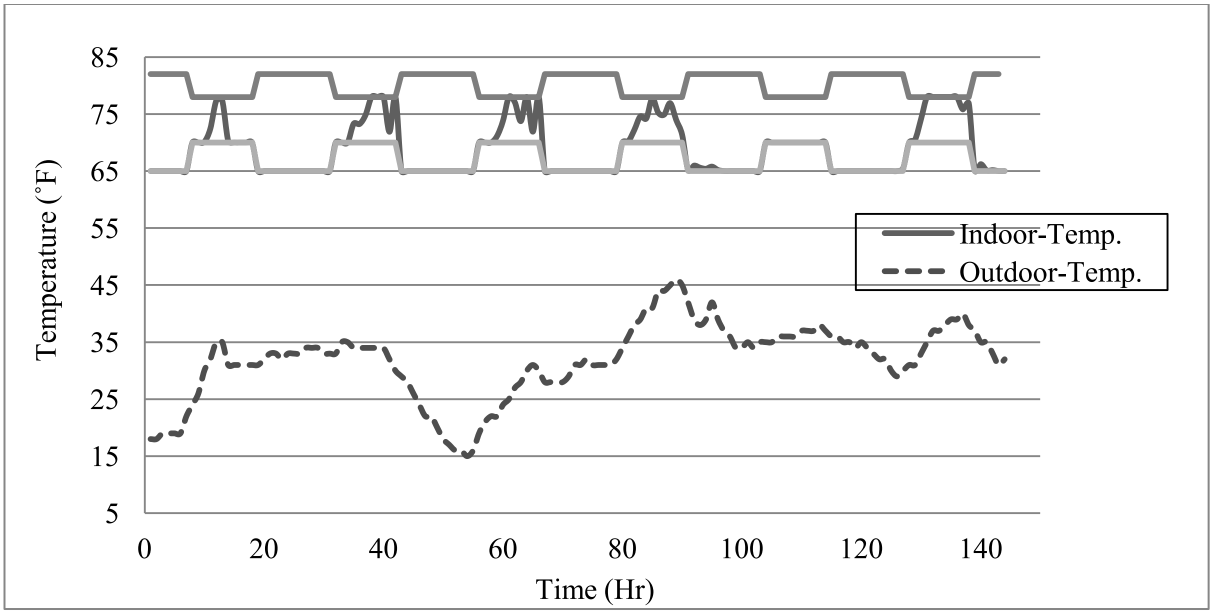
6.6.1 Developing rules for rule-Base decision making

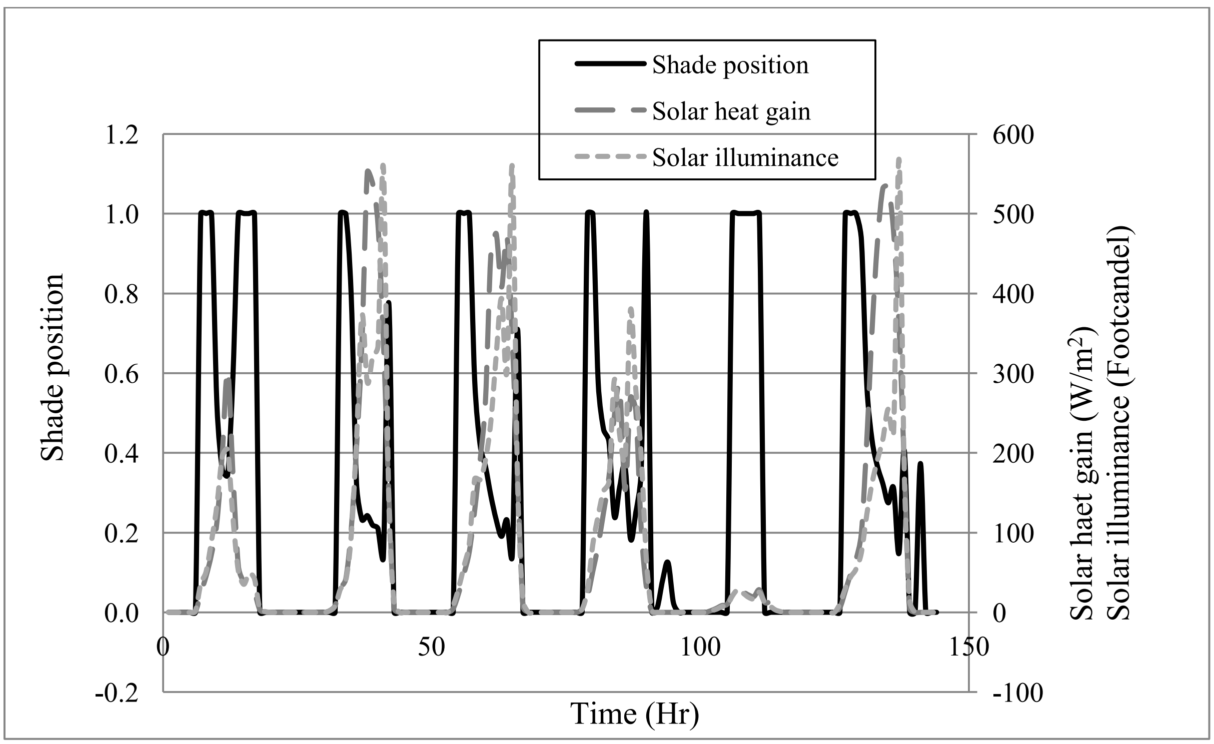
Optimization of energy and peak load depends on finding the right combination of control parameters such as indoor temperature, shade position, light power, and outdoor air fan flow rates. Investigating optimized value of these control parameters leads to better understanding of building energy optimization process and developing new rules for decision making algorithm before optimization. Figure 6-30 shows the results of indoor temperature and shade position for four zones in transient season in April 1 to April 6. For better comparison results of the indoor temperatures are demonstrated with the outdoor temperature. Also, results of the shade positions for each zone are demonstrated with the solar heat gain and the solar illuminance from that zone window.

Developed decision making rules are introduced below: these are obtained based on investigated control parameters results. Values of the constraints depend on building envelope and systems.

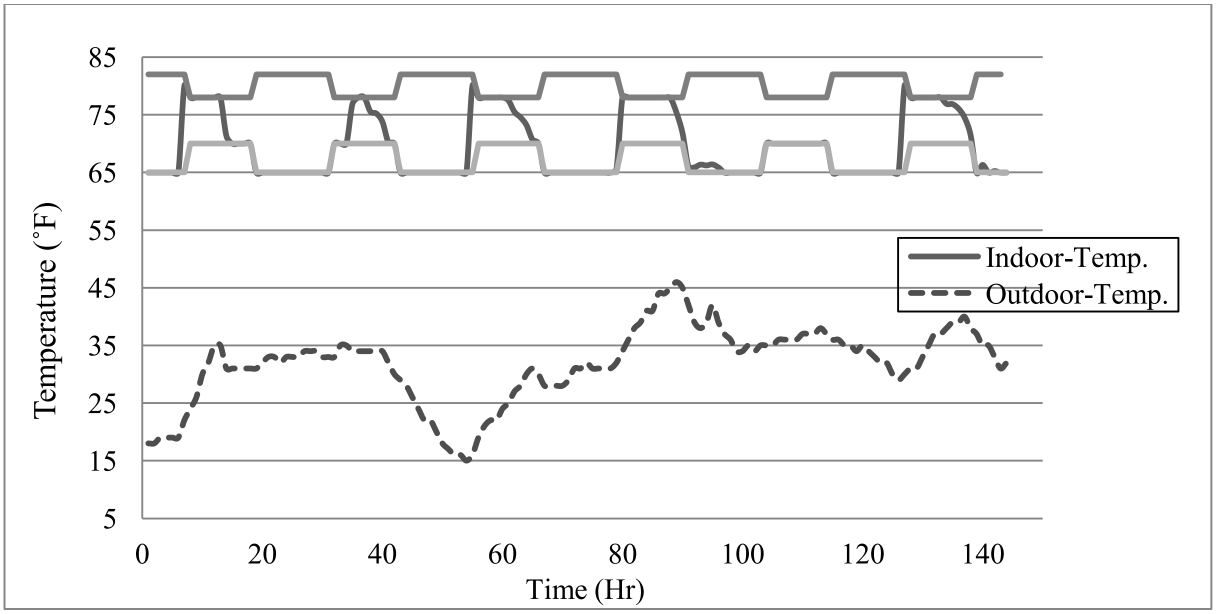
- In very cold and very hot outdoor temperatures, indoor temperature should be kept in its extremums.

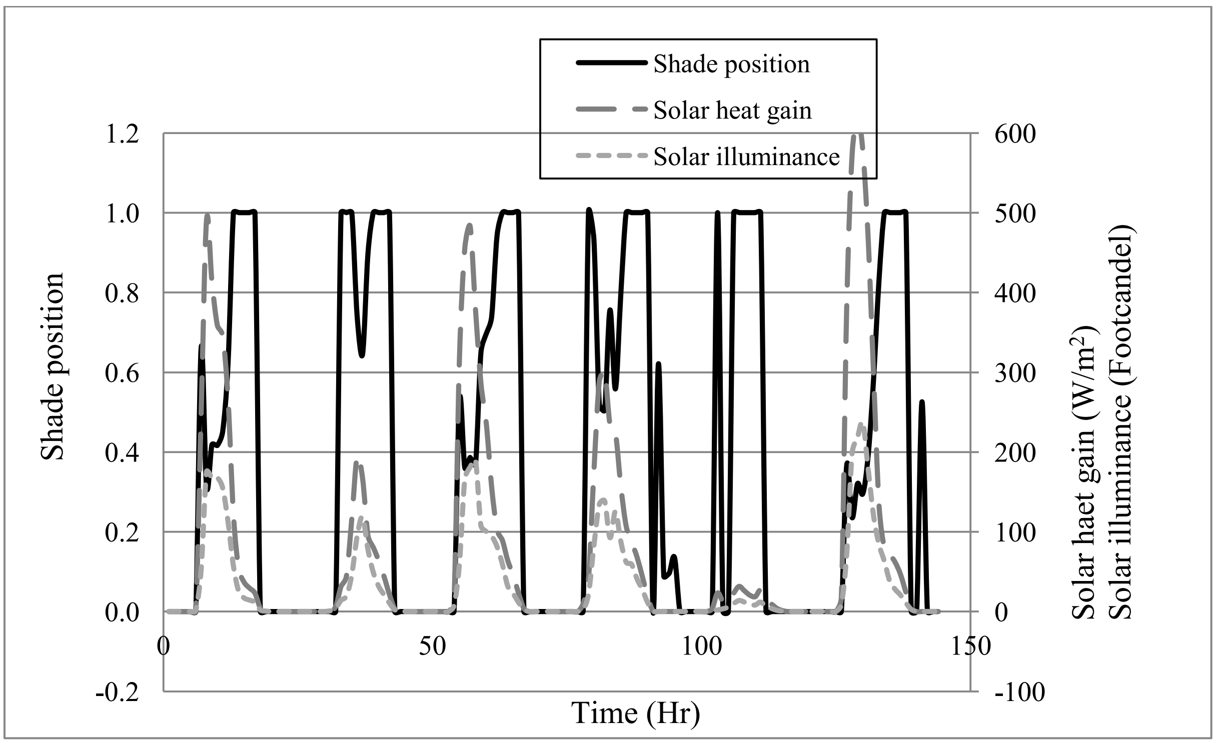
  The Figure 6-31 shows the results of integrated optimal control for indoor temperature based on outdoor temperature. For investigated office building in Montreal the indoor temperature should be kept at its minimum for outdoor temperature lower than -5 ˚C and it should be kept at its maximum for outdoor temperature higher than 21 ˚C.



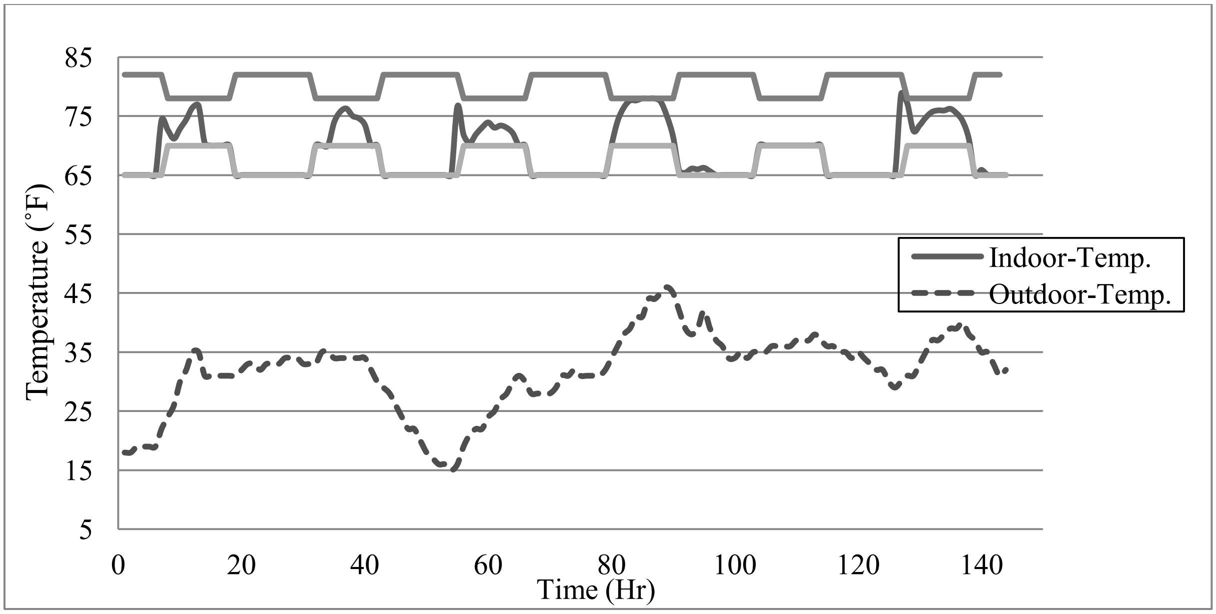


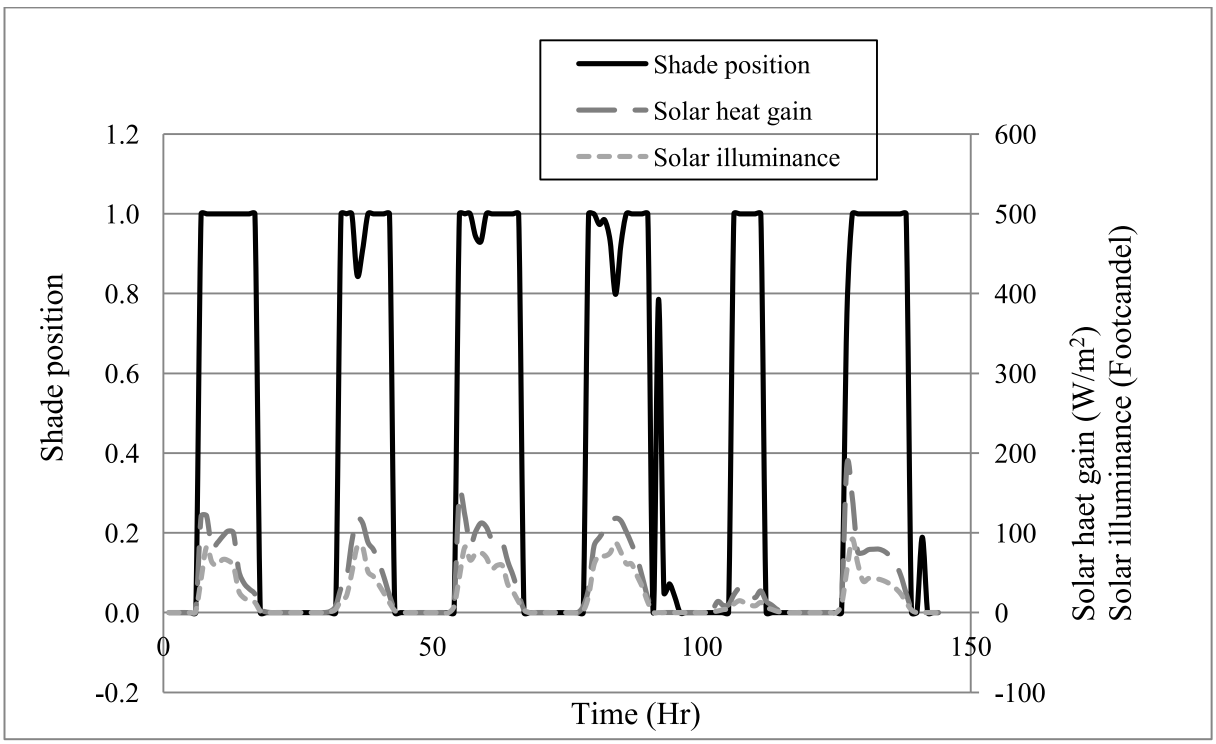
Zone 1 - South side



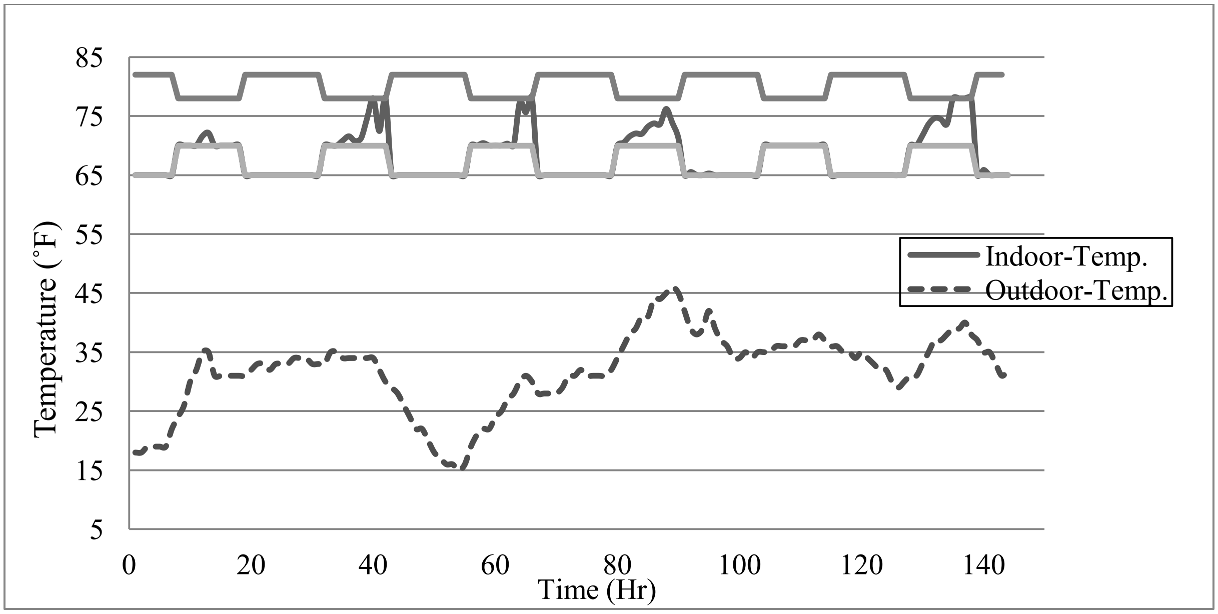


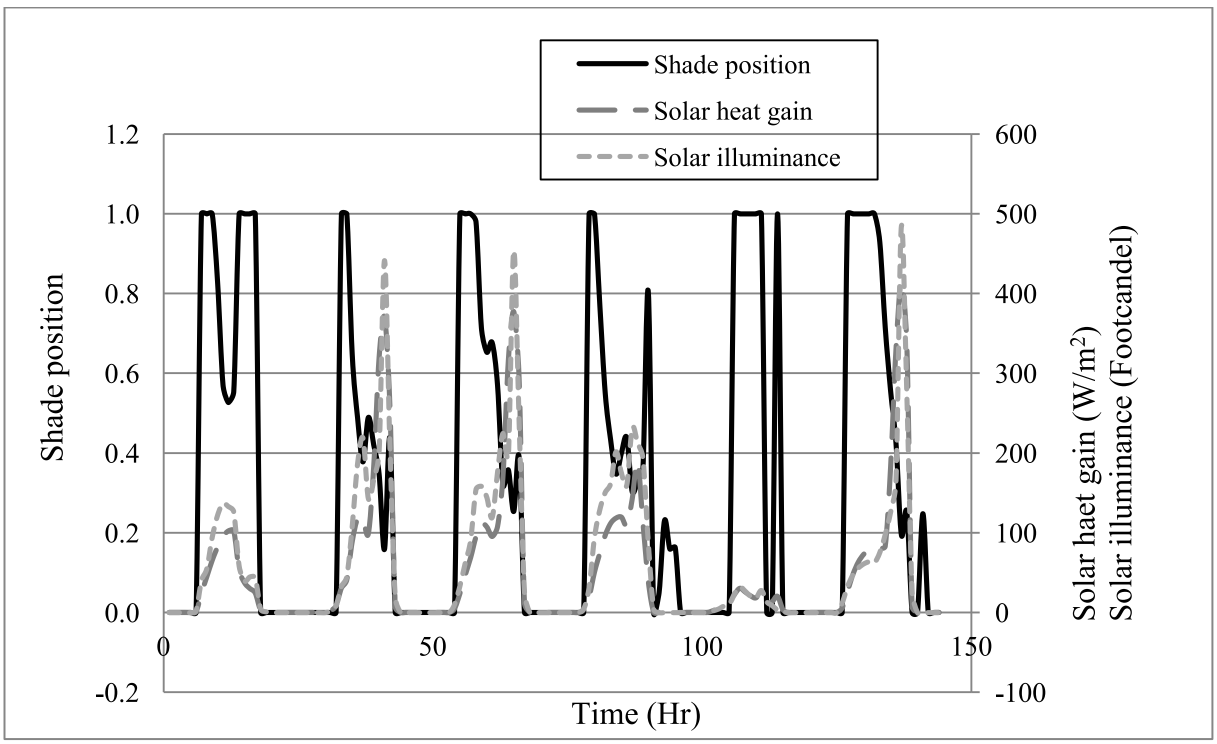
Zone 2 – East side





Zone 3 – North side





Zone 4 – West side

Figure 6-30: Results of the indoor temperature and outdoor temperature, as well as, shade position, solar heat gain, and solar illuminance for each zone from April 1 to April 6

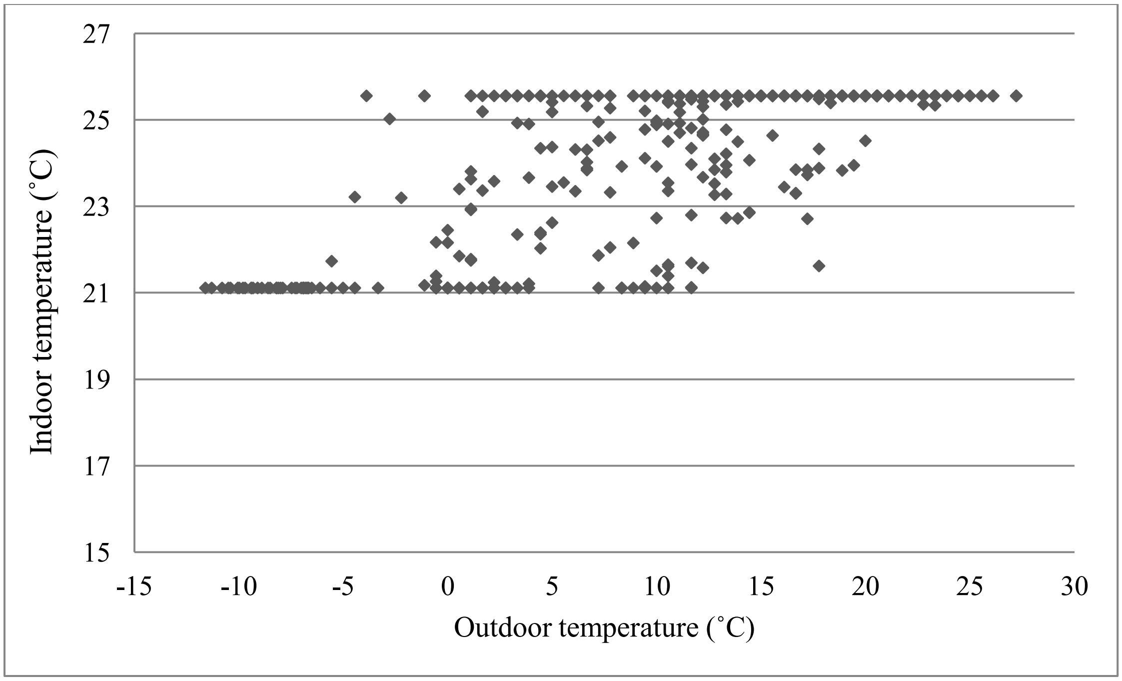


Figure 6-31: Results of optimized indoor temperature based on outdoor temperature

- In very cold and very hot outdoor temperatures, shade position should be closed.
- In cooling seasons with mild outdoor temperature, it is most suitable to keep shade position open.

The results of optimized shade position of sample office building versus outdoor temperature show that shade position should be kept closed for outdoor temperature higher than 20 ˚C and lower than -20 ˚C. Also, for outdoor temperature between 0 ˚C and 10 ˚C open shade position leads to higher energy savings for integrated optimal control (Figure 6-32).

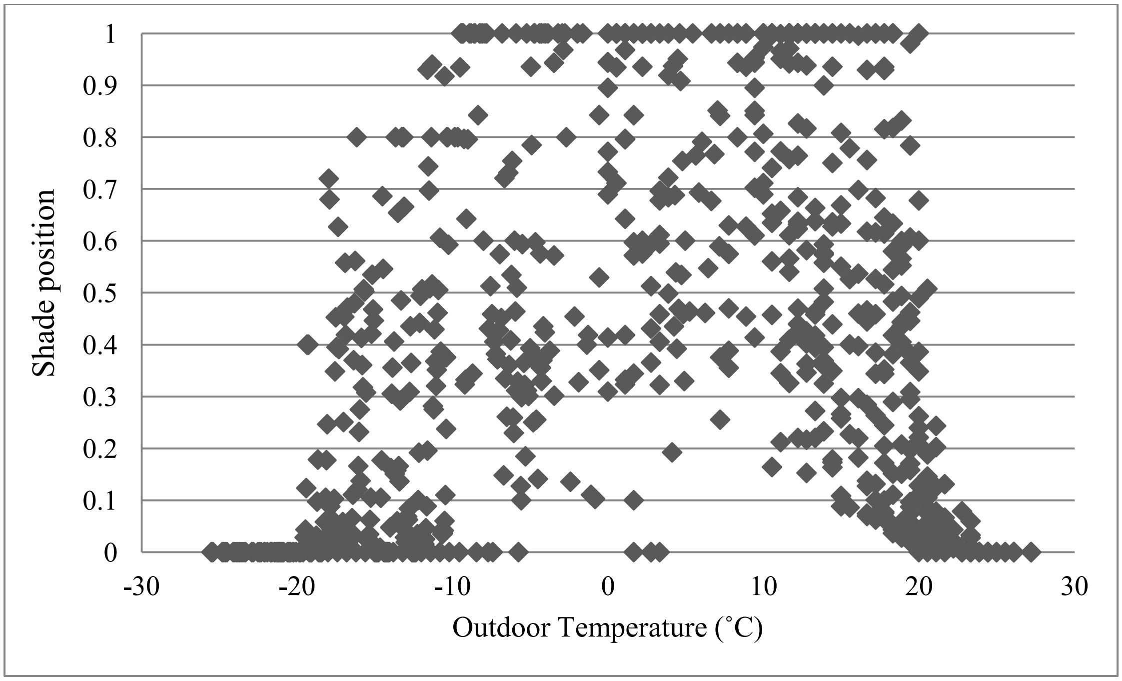


Figure 6-32: Results of optimized shade position based on outdoor temperature

- In very cold and very hot outdoor temperatures, outdoor air fan flow rate should be kept at its minimum.
- Outdoor air fan flow rate could be kept at higher rate during cooling season when outdoor air is lower than indoor temperature with proper temperature difference.

Figure 6-33 shows the results of outdoor air fan flow rate versus outdoor temperature in sample office building in Montreal. For outdoor temperature higher than 22 ˚C and lower than 2 ˚C fan flow rate should be kept at minimum amount.

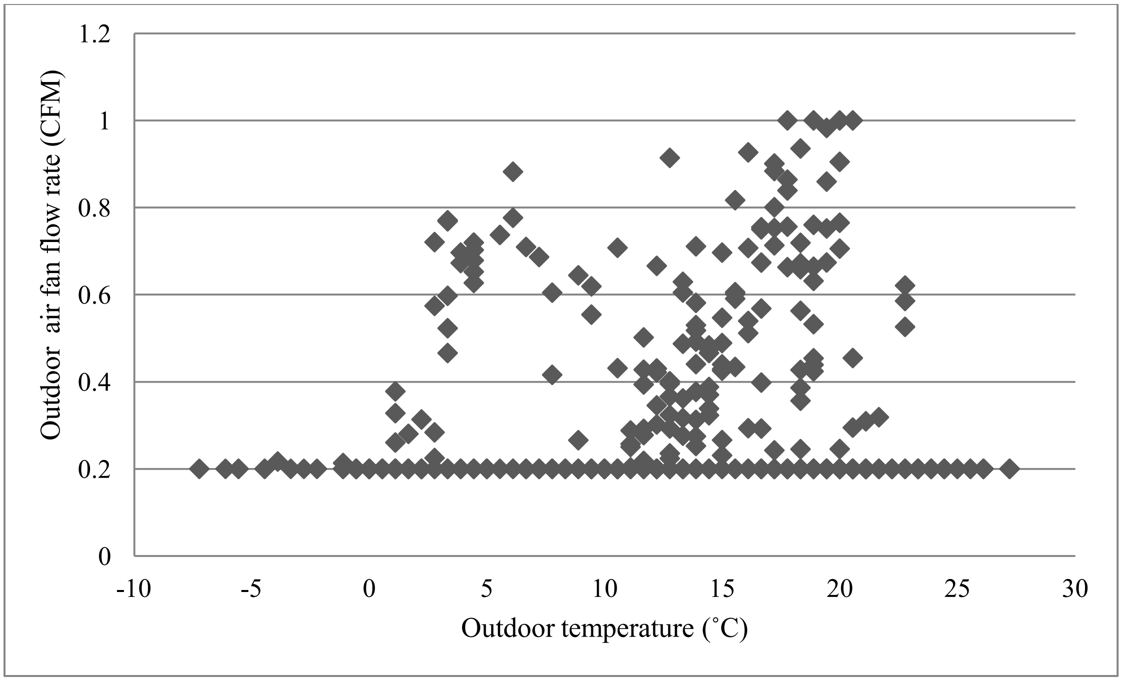


Figure 6-33: Results of optimized fan flow rate based on outdoor temperature

Comparing similar results of shade position and zones orientation in figure 6-28 for entire year show that

- Zone in North side of the building receives lower solar heat gain and illuminance and shade position has small effect in zone load calculation
- Zone in East side of the building receives higher solar heat gain and illuminance during the morning and shade position is more effective than the afternoon.
- Zone in West side of the building receives higher solar heat gain and illuminance during the afternoon and shade position is more effective than the morning.

6.6.2 Multi-hour integrated optimization

Applying multi-hour optimization increases energy savings potential by considering effect of current hour on future hour energy consumption and energy storage possibility of the building.

Figure 6-34 and Figure 6-35 show the energy and cost savings potential of multi-hour optimization. In these cases multi-hour optimization tries to adjust the indoor temperature of the current hour with respect to future hour preference. Also it tries to shift energy consumption from peak hours to off-peak hours.

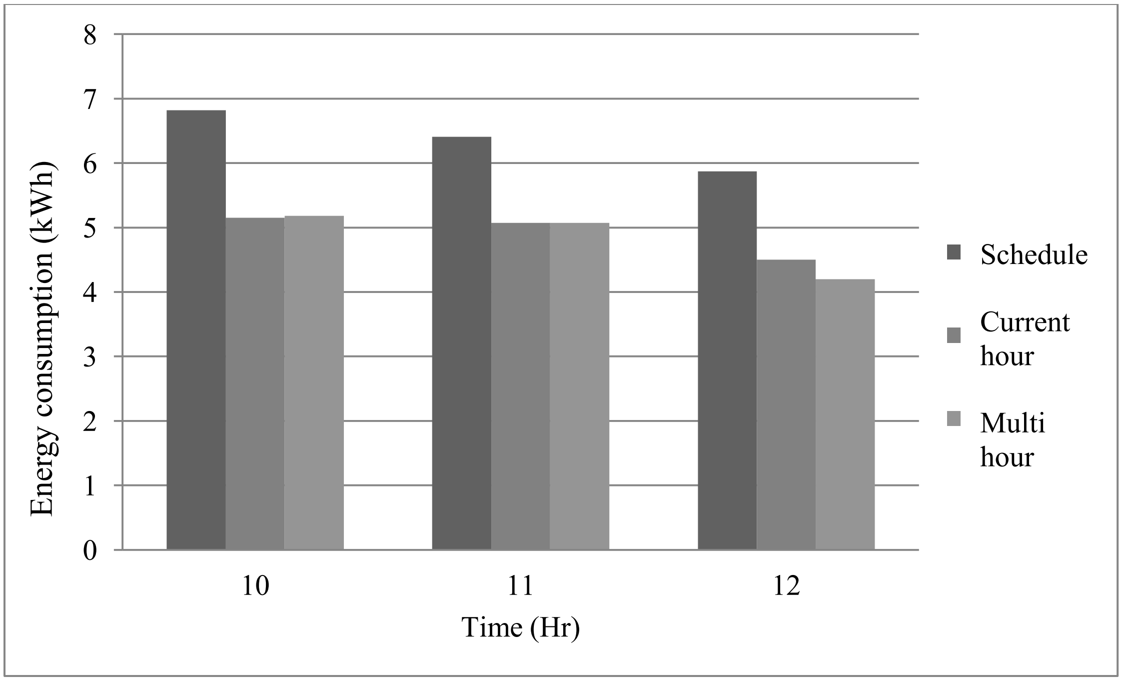


Figure 6-34: Sample energy savings potential of multi hour optimization of May 3, hours 10 to 12

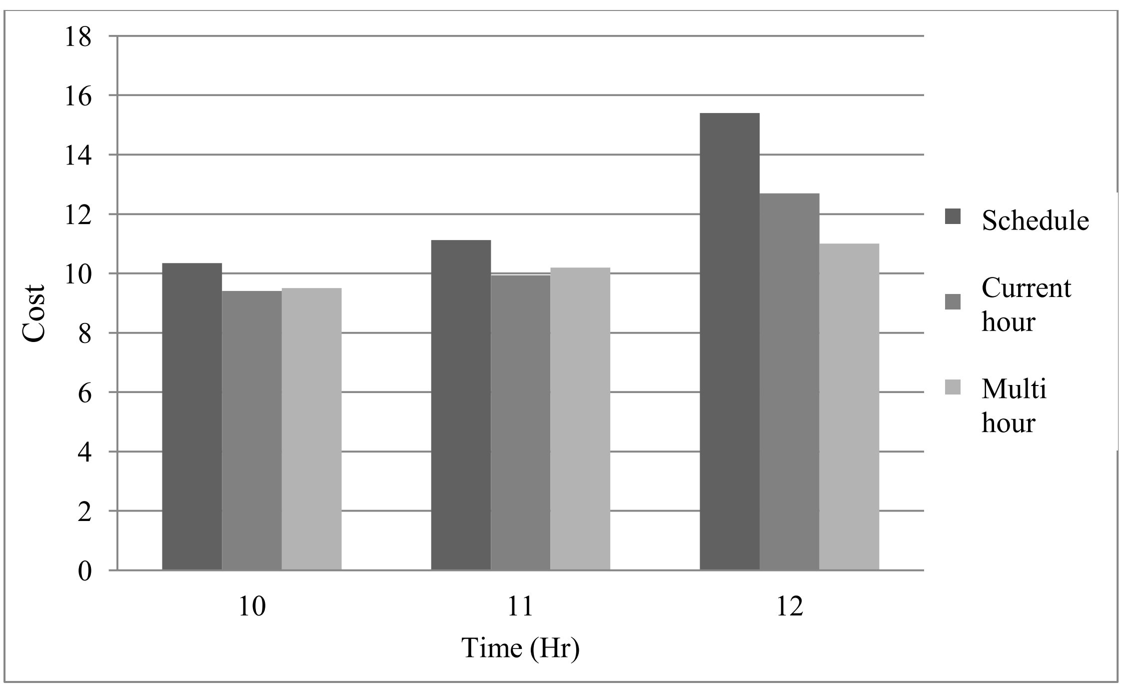


Figure 6-35: Sample cost saving potential of multi hour optimization of August 18, hours 10 to 12

Figure 6-36 shows the results of multi-hour energy optimization. Increasing the period of multi-hour optimization increases the energy savings potential but decreases the speed and accuracy of optimization and increases the chance of divergence. As a result, considering more than 3 hours for multi-hour optimization is neither accessible nor accurate. By using more than 3 hours unacceptable results and divergence occurred more than the allowable amount and the results are not reliable anymore.

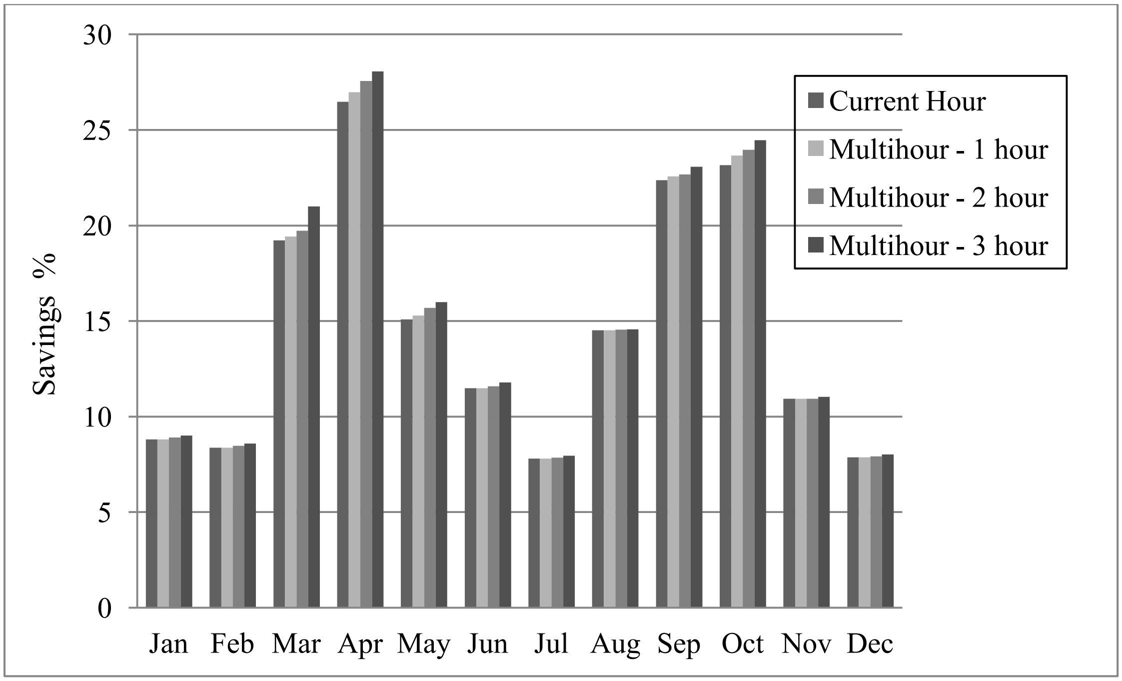


Figure 6-36: Building total energy savings for different months with current hour and multi hour integrated optimization

7 Conclusion and Remarks

Building system operations are critical to optimizing energy use, reducing energy and maintenance costs, ensuring occupant comfort and maintaining the quality of indoor air. Today's buildings are complex and have interdependent systems that require sophisticated controls. Optimizing a building's energy consumption requires an approach that allows devices and systems to work together, while considering their effect on each other in an efficient and cost-effective way to meet occupant requirements and expectations.

Many buildings have multiple systems that typically work independently of each other. These systems include heating, cooling, lighting, ventilation, automated blinds, and domestic hot water. The control strategies of existing building systems usually do not work at their fullest potentials. These control methods lead to poor energy management and comfort. Comprehensive integrated algorithms for building control are not completely investigated yet. Although the previous researches tried to control different effective parameters in one or multiple zones, some limitations in those researches (about all possible strategies and effective parameters and methods of optimization) highlight the need for a more accurate and efficient integrated control.

The main interest of this research is to develop an advanced building operation system for integrated control of lighting, blinds, ventilation and heating and cooling systems for whole buildings, in order to

1) Improve the indoor environment (thermal comfort, visual comfort and air quality)
2) Reduce operation cost (energy consumption, energy price and maintenance)
3) Reduce peak load (response to peak demand charge and time-of-use rates)

Also, effect of current hour parameters on future hour energy consumption is considered by multi-hour optimization. In addition, approaches are developed to coordinate integrated control and demand response and develop new rules that help whole building control.

Three main steps to reach the objective of the research are:

- Optimization of building energy consumption based on developed RC-network model
- Modification of simulation tool (DOE-2) by adding specific functions for investigation of all strategies and control parameters
- Integration of optimization method and energy simulation software, as well as increasing speed of optimization

An RC-network model of a typical one-story office building is developed and created in MATLAB. Building control parameters of temperature, light, shade position and outdoor fan flow rate are optimized by using a nonlinear optimization method and results compared with scheduled control of the same building. Yearly energy savings of about 35% is achieved by using integrated control instead of scheduled control. The results show that the amount of energy saved by controlling the shade based on heating and cooling is more than the amount of energy saved by controlling the shade based on indoor illuminance. In addition, by using individual zone control energy savings will be reduced between 1% and 10%. Also, multi-hour optimization saves up to 4% of energy cost compared to optimization, based on the current hour for mentioned days.

DOE-2 as an open source building simulation software is chosen for the building energy and cost calculation method. This software required some modification for satisfying integrated optimization requirements. DOE-2 required predefining of all building and control variables before yearly optimization; it is modified to accept control parameters from optimization methods and also to receive previous hour building control parameters and indoor conditions as an input, which made it possible to do online and hourly simulation and optimization. In addition, the shade position simulation method of DOE-2 was modified to calculate energy consumption of the building based on shade position instead of just with open or closed shade. The results of using the modified DOE-2 for controlling nighttime ventilation show nearly 5% energy savings with medium and high building thermal mass in Montreal. Also, simulations with different temperature difference between inside and outside air show that when outdoor temperature is approximately 5.5 °C (10 °F) lower than indoor temperature, nighttime ventilation works more efficiently.

The integrated optimization tool is developed based on connecting DOE-2 and the optimization method in MATLAB. Several methods such as applying the rule-based decision-making method before optimization with a GA, in addition to training the neural network for optimization and using local search after the GA, are introduced to increase optimization speed and accuracy.

Application of the developed integrated optimization tool on nighttime ventilation and shade position optimization are investigated for comparison and validation. The results for nighttime ventilation show total energy savings up to 8% and cooling energy consumption up to 23%. These savings occurred on days with high diurnal temperature range and average temperature near 17 ˚C. Higher energy savings are calculated for days with an outdoor average temperature between 15 ˚C and 22 ˚C. The results for shade position optimization show that on very cold days shades stay closed, since the effect of conduction heat transfer is more significant than solar heat gain and illuminance transmission from windows. Also on very hot days, in addition to the detrimental effect of conduction heat transfer, shades stay nearly closed, since the effect of solar heat gain which increases cooling energy consumption is more pronounced and important than lighting energy reduction from daylighting. In transient seasons when the building is in heating mode, shades stay mostly open, since heat gain and illuminance transmission from windows reduces both heating and lighting energy consumption. Results show that using thick shades, lower light energy consumption and lower illuminance set-point give optimization more flexibility for energy savings.

Finally, the developed integrated tool for whole building energy optimization was applied to a typical office building in Montreal. The results show energy savings between 10% and 30%; also higher energy savings potential could be expected during transient seasons compared to very hot or very cold seasons. The results also show peak load savings from 21% to 43%. Applying multi-hour optimization increases energy savings potential by considering the effect of the current hour on future hour energy consumption and energy storage possibility of the building. Increasing the period of multi-hour optimization increases the energy savings potential but decreases the speed and accuracy of optimization and increases the chance of divergence.

7.1 Contributions

This reseach advances the investigation and development of integrated building control optimization through the following contributions:

1. Developing a basic building-integrated optimization to investigate effective control parameters and characterize the effect of integrated control on building energy consumption. The integrated building control optimization based on a developed RC-network model provides a fast and tolerable tool to researchers for investigating different parameters and approaches for optimization of building energy consumption.

2. Introducing required modification in building energy and cost calculation software to prepare it for using in the real-time optimization process. The set of modifications that are applied to DOE-2 as a building energy calculation software to use for real-time integrated control can provide a guideline for modifying other building energy calculation software in other research.

3. Developing an algorithm to connect any optimization methods (MATLAB) with building energy calculation software with text format of input and output. The methodology that is used for connecting a genetic algorithm in MATLAB and DOE-2 can be used by researchers for developing their optimization tools with other methods or in other applications.

4. Introducing a systematic approach for increasing speed of optimization in building integrated control optimization. Investigation of using a decision-making algorithm before global optimization and using local search after global optimization provides a framework for developing a fast and accurate integrated optimization method.

5. Presenting a set of rule-based recommendations for whole building integrated control. Possibility of developing decision-making rules for building integrated control based on integrated control optimization results provides the opportunity to decrease building energy consumption even without a real-time optimization tool. Also these rules increase the speed of real-time optimization significantly by decreasing the optimization domain.

Based on the developments and investigations of this thesis, several papers are published, including journals papers:

- Aria and Akbari, "Integrated and multi-hour optimization of office building energy consumption and expenditure," *Energy and Building Journal* (2014).
- Aria and Akbari, "Optimisation of night-time ventilation parameters to reduce building's energy consumption by integrating DOE-2 and MATLAB," *International Journal of Sustainable Energy* (2014).
- Aria and Akbari, "A predictive nighttime ventilation algorithm to reduce energy use and peak demand in an office building," *Journal of Energy and Power Engineering* (2013).

7.2 Future works

As is discussed in this thesis, a framework is introduced for integrated building control optimization, and the optimization tool is developed and applied in a typical office building in Montreal. The results show significant energy consumption and peak load reduction compared to fixed-schedule building control. Simulating different types of buildings in more cities and comparing the building energy consumption results as a future work would be beneficial to evaluate possible energy savings potential of integrated control and to develop new rules for the decision-making section. Multi-hour optimization for integrated control of a whole building investigated up to the next three hours, since considering more future-hours was very time-consuming or increased optimization divergence probability. As a future work, using a high-speed computer for simulating multi-hour optimization with more time periods and higher numbers of iteration could lead to higher savings. Developed control optimizations are evaluated and validated by comparing their applications (nighttime ventilation and shade position optimization) with similar cases. As a future work, the developed optimization tool could be applied in real buildings to have experimental results for validation of simulated results. In addition, Adding objective function of occupancy comfort and using multi-objective optimization can be considered as a future work.

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Appendix A: Nonlinear optimization based on RC-network model MATLAB program

This program optimizes a five zones building energy consumption based on RC-network model by using nonlinear optimization. The flowchart of this program, RC-network model of entire building, and parameters values are shown in below.

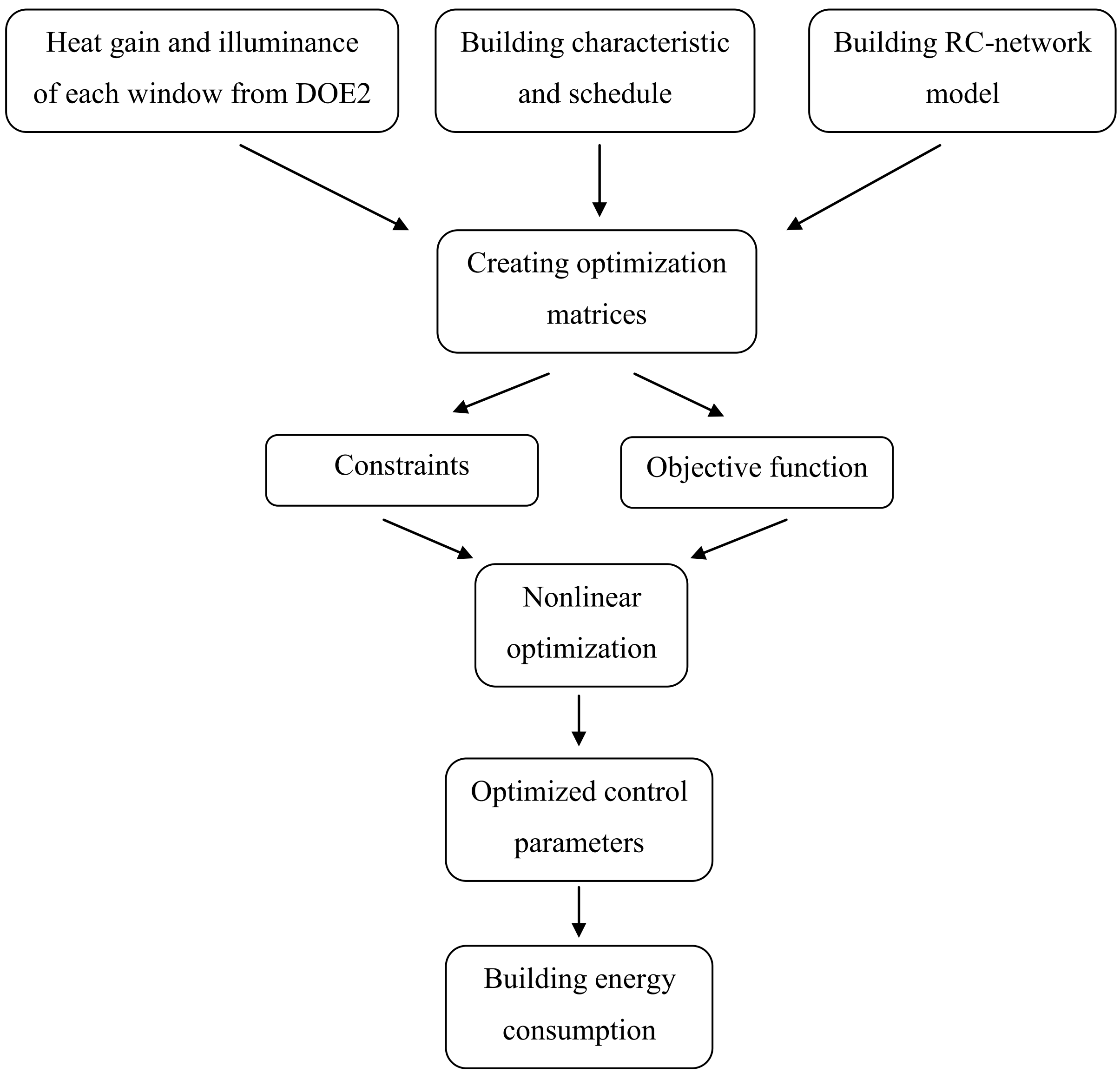


Figure A-1: Program flowchart

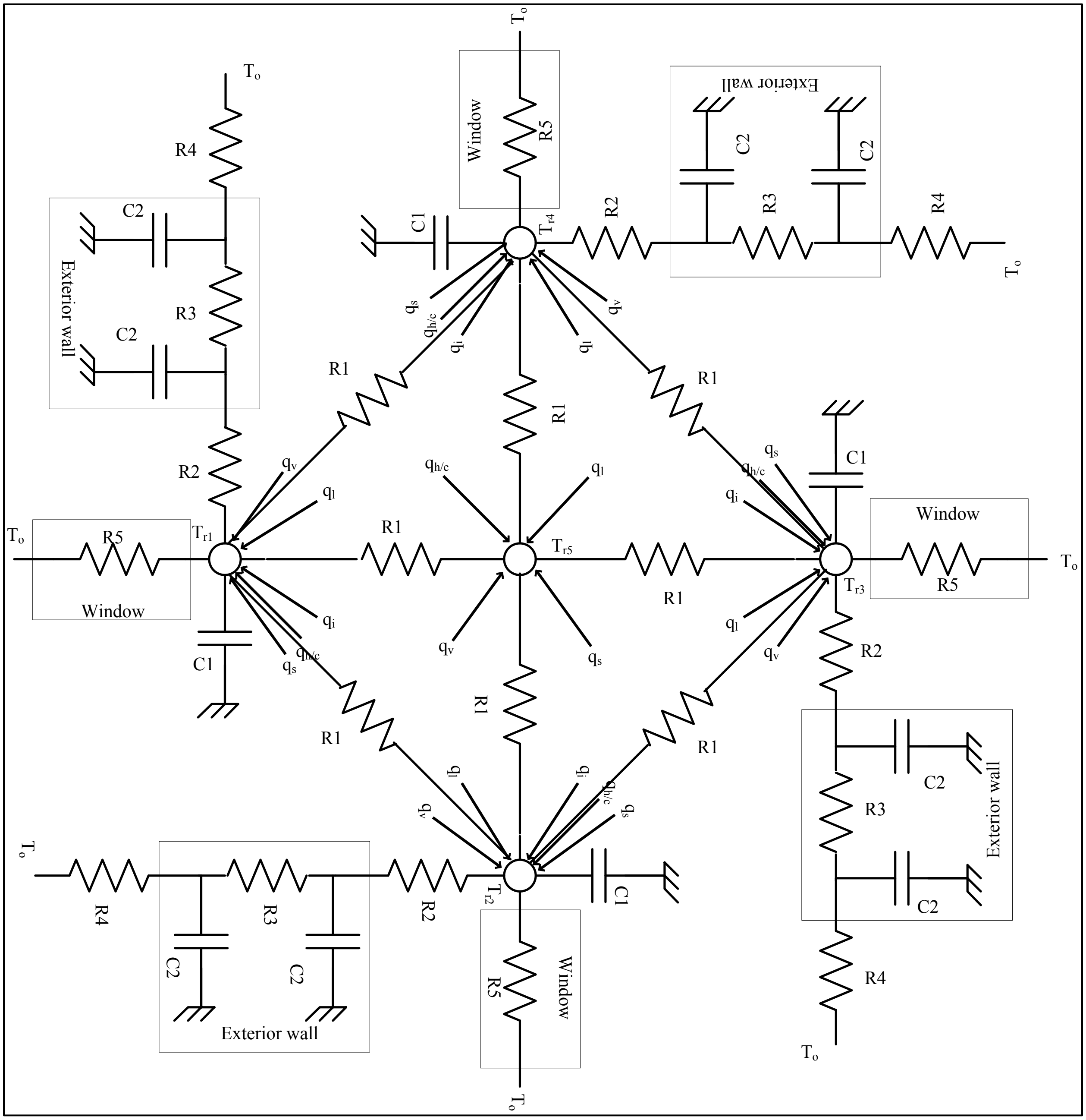


Figure A-2: Building RC-network model

Table A-1: Detail of building construction and systems

Building parameters	**Value**
Chiller COP	3.5
Electrical heater efficiency	1
Open shade window U value	2.3 W/m^2 K (0.4 Btu/hr ft^2 °F)
Close shade window U value	1.4 W/m^2 K (0.25 Btu/hr ft^2 °F)
Fluorescent lamp efficacy	70 lumens/W
Exterior wall U value	0.4 W/m^2 K (0.073 Btu/hr ft^2 °F)
Exterior wall specific heat	42 kJ/kg K (10 Btu/ °F lb)
Exterior wall outdoor surface convection heat coefficient	34 W/m^2 K (6 Btu/hr ft^2 °F)
Exterior wall indoor surface convection heat coefficient	8.5 W/m^2 K (1.5 Btu/hr ft^2 °F)
Interior wall U value	1.53 W/m^2 K (0.27 Btu/hr ft^2 °F)
Fan energy consumption	0.88 W (3 Btu/hr) per CFM of air
Maximum lamp power	15.8 W/m^2 (1.5 W /ft^2)

Table A-2: Building schedule

Schedule	**Occupied**	**Un-occupied**
Minimum indoor illuminance	753.5 lux (70 Foot-candle)	430.5 lux (40 Foot-candle)
Occupancy heat generation	12.6 W/m^2 (4 Btu/hr ft^2)	1.6 W/m^2 (0.5 Btu/hr ft^2)
Equipment heat generation	10.7 W/m^2 (3.4 Btu/hr ft^2)	3 W/m^2 (1 Btu/hr ft^2)
Cooling temperature set-point	25.5 °C (78 °F)	26.6 °C (80 °F)
Heating temperature set-point	21 °C (70 °F)	18.3 °C (65 °F)
Minimum fresh air flow rate	0.01 m^3/s per m^2 (0.2 CFM per ft^2)	0.003 m^3/s per m^2 (0.05 CFM per ft^2)

```
function RCnetwork_Nonlinear
clc
clear all
% Properties
COP=3.5;Uo=0.4;Uc=0.25;Eff=70;
ILLsp=70;MAXlp=5;Equ=3.4;Occ=4;
Uw=0.069;Bv=0.25;Av=3;EtaH=1;
rho=0.08;CP=0.24;

% read input data of temperature, window heat gain and illuminance for all
% zones
fid = fopen('Inout.txt');
P = fscanf(fid, '%g %g', [12 inf]);
P=P';
n=24;
h=31;
T=70*ones(n*h,38);
ET=0;
EE=0;
EH=0;
for r=0:(h-1)

   for i=1:n
        % Properties and inputs
        COP=3.5;Uo=0.4;Uc=0.25;Eff=70;
        ILLsp=70;MAXlp=5;Equ=3.4;Occ=4;
        Uw=0.069;Bv=0.25;Av=3;EtaH=1;
        rho=0.08;CP=0.24;
        rhow=8;CPw=10;L=0.2;hi=1.5;ho=6;
        Uw1=0.0732;Tii=67;
       % Calculating elements of optimization matrices
        if i<=8 || i>=19
           ILLsp=40;Equ=1;Occ=0.5;
        end
        for j=1:4
           D(i+(24*r),10*(j-1)+1:10*j)=[MAXlp,(Uo-Uc),(Uc+hi)+rho*8*CP,-
MAXlp,...
                -((Uo-Uc)*P(i+(24*r),1+3*(j-1))+P(i+(24*r),2+3*(j-1))),...
                rho*CP*60*P(i+(24*r),1+3*(j-1)),...
                rho*CP*60,MAXlp*Eff/3.4,P(i+(24*r),3+3*(j-1)),ILLsp];
           D(i+(24*r),53)=rho*8*CP;%D53
          if i+(24*r)==1
            K(i+(24*r),j)=((Uc)*P(i+(24*r),1+3*(j-1))+Occ+Equ+rho*8*CP*Tii);
            K(i+(24*r),5)=(Occ+Equ+rho*8*CP*Tii);
          else
            K(i+(24*r),j)=((Uc)*P(i+(24*r),1+3*(j-
1))+Occ+Equ+rho*8*CP*T(i+(24*r)-1,5+8*(j-1)));
            K(i+(24*r),5)=(Occ+Equ+rho*8*CP*T(i+(24*r)-1,32+3));
          end
        end
   end

 % Building set-point
   for i=1:n

        if i==1
```

```
            Tcs(i+(24*r),1:5)=80;Ths(i+(24*r),1:5)=65;cfm(i+(24*r),1:5)=0.05;
        elseif i<=7 || i>=20
            for j=1:4
            Tcs(i+(24*r),j)=min(80,T(i+(24*r)-1,5+8*(j-1))+3);
            Ths(i+(24*r),j)=max(65,T(i+(24*r)-1,5+8*(j-1))-3);
            end
            Tcs(i+(24*r),5)=min(80,T(i+(24*r)-1,3+32)+3);
            Ths(i+(24*r),5)=max(65,T(i+(24*r)-1,3+32)-3);
            cfm(i+(24*r),1:5)=0.05;
        elseif i==8
            Tcs(i+(24*r),1:5)=78;Ths(i+(24*r),1:5)=70;cfm(i+(24*r),1:5)=0.2;
        elseif i==19
            Tcs(i+(24*r),1:5)=80;Ths(i+(24*r),1:5)=65;cfm(i+(24*r),1:5)=0.2;
        else
            for j=1:4
            Tcs(i+(24*r),j)=min(78,T(i+(24*r)-1,5+8*(j-1))+3);
            Ths(i+(24*r),j)=max(70,T(i+(24*r)-1,5+8*(j-1))-3);
            end
            Tcs(i+(24*r),5)=min(78,T(i+(24*r)-1,3+32)+3);
            Ths(i+(24*r),5)=max(70,T(i+(24*r)-1,3+32)-3);
            cfm(i+(24*r),1:5)=0.2;
        end
end
% Solver loop
    for i=1:n
      % Properties
      COP=3.5;Uo=0.4;Uc=0.25;Eff=70;
      ILLsp=70;MAXlp=5;Equ=3.4;Occ=4;
      Uw=0.069;Bv=0.25;Av=3;EtaH=1;
      rho=0.08;CP=0.24;
      rhow=8;CPw=10;L=0.2;hi=1.5;ho=6;
      Uw1=0.0732;    Tii=67;
     if i<=8 || i>=19
         ILLsp=40;Equ=1;Occ=0.5;
     end
%     --------------------------------------------------------------------
     for j=1:4
        if i+(24*r)==1
            K(i+(24*r),j)=((Uc)*P(i+(24*r),1+3*(j-1))+Occ+Equ+rho*8*CP*Tii);
            K(i+(24*r),5)=(Occ+Equ+rho*8*CP*Tii);
        else
            K(i+(24*r),j)=((Uc)*P(i+(24*r),1+3*(j-
1))+Occ+Equ+rho*8*CP*T(i+(24*r)-1,5+8*(j-1)));
            K(i+(24*r),5)=(Occ+Equ+rho*8*CP*T(i+(24*r)-1,32+3));
        end
     end
     if i==1
         Tcs(i+(24*r),1:5)=80;Ths(i+(24*r),1:5)=65;cfm(i+(24*r),1:5)=0.05;
     elseif i<=7 || i>=20
            for j=1:4
                Tcs(i+(24*r),j)=min(80,T(i+(24*r)-1,5+8*(j-1))+3);
                Ths(i+(24*r),j)=max(65,T(i+(24*r)-1,5+8*(j-1))-3);
            end
            Tcs(i+(24*r),5)=min(80,T(i+(24*r)-1,3+32)+3);
            Ths(i+(24*r),5)=max(65,T(i+(24*r)-1,3+32)-3);
            cfm(i+(24*r),1:5)=0.05;
     elseif i==8
```

```
            Tcs(i+(24*r),1:5)=78;Ths(i+(24*r),1:5)=70;cfm(i+(24*r),1:5)=0.2;
        elseif i==19
            Tcs(i+(24*r),1:5)=80;Ths(i+(24*r),1:5)=65;cfm(i+(24*r),1:5)=0.2;
        else
            for j=1:4
              Tcs(i+(24*r),j)=min(78,T(i+(24*r)-1,5+8*(j-1))+3);
              Ths(i+(24*r),j)=max(70,T(i+(24*r)-1,5+8*(j-1))-3);
            end
            Tcs(i+(24*r),5)=min(78,T(i+(24*r)-1,3+32)+3);
            Ths(i+(24*r),5)=max(70,T(i+(24*r)-1,3+32)-3);
            cfm(i+(24*r),1:5)=0.2;
        end
 %-------------------------------------------------------------------------
% Start point
    Xst=[zeros(1,4),70,0.2,70,P(i,1)];
    xstart=[Xst,Xst,Xst,Xst,0,0,70,0.2];

% Creating the optimization matrices

    aa=zeros(3,8);aa(1,1)=1;aa(2,2)=1;aa(3,5)=1;
    Ap=[blkdiag(aa,aa,aa,aa),zeros(12,4);zeros(1,34),1,0];
    aap=zeros(4,8);

% Matrix A
    for j=1:4
         aap(j,:)=[-D(i+(24*r),8+10*(j-1)),-D(i+(24*r),9+10*(j-
1)),zeros(1,6)];
    end
    App=[blkdiag(aap(1,:),aap(2,:),aap(3,:),aap(4,:)),zeros(4,4)];
    A=[Ap;App];
% Creating matrices b, lb

b=[1;1;Tcs(i+(24*r),1);1;1;Tcs(i+(24*r),2);1;1;Tcs(i+(24*r),3);1;1;Tcs(i+(24*
r),4);Tcs(i+(24*r),5);-D(i+(24*r),10);-D(i+(24*r),20);-D(i+(24*r),30);-
D(i+(24*r),40)];
    lb=[0 0 0 0 Ths(i+(24*r),1) cfm(i+(24*r),1) -20 -20 0 0 0 0
Ths(i+(24*r),2) cfm(i+(24*r),2) -20 -20 0 0 0 0 Ths(i+(24*r),3)
cfm(i+(24*r),3) -20 -20 0 0 0 0 Ths(i+(24*r),4) cfm(i+(24*r),4) -20 -20 0 0
Ths(i+(24*r),5) cfm(i+(24*r),5)];
% Creating Aeq
       Aeq=[0 0 0 0 -hi 0 rhow*CPw*L+Uw1+hi -Uw1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 -Uw1 rhow*CPw*L+Uw1+ho 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 -hi 0 rhow*CPw*L+Uw1+hi -Uw1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 0 0 -Uw1 rhow*CPw*L+Uw1+ho 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 -hi 0 rhow*CPw*L+Uw1+hi
-Uw1 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 -Uw1
rhow*CPw*L+Uw1+ho 0 0 0 0 0 0 0 0 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 -hi 0
rhow*CPw*L+Uw1+hi -Uw1 0 0 0 0
             0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 -Uw1
rhow*CPw*L+Uw1+ho 0 0 0 0];
```

```
% Creating beq
     if i+(24*r)==1

beq=[rhow*CPw*L*Tii;rhow*CPw*L*P(i+(24*r),1)+P(i+(24*r),1)*ho;rhow*CPw*L*Tii;
rhow*CPw*L*P(i+(24*r),1+3)+P(i+(24*r),1+3)*ho;rhow*CPw*L*Tii;rhow*CPw*L*P(i+(
24*r),1+6)+P(i+(24*r),1+6)*ho;rhow*CPw*L*Tii;rhow*CPw*L*P(i+(24*r),1+9)+P(i+(
24*r),1+9)*ho];
     else
         beq=[rhow*CPw*L*T(i+(24*r)-1,7);rhow*CPw*L*T(i+(24*r)-
1,8)+P(i+(24*r),1)*ho;rhow*CPw*L*T(i+(24*r)-1,7+8);rhow*CPw*L*T(i+(24*r)-
1,8+8)+P(i+(24*r),1+3)*ho;rhow*CPw*L*T(i+(24*r)-
1,7+16);rhow*CPw*L*T(i+(24*r)-
1,8+16)+P(i+(24*r),1+6)*ho;rhow*CPw*L*T(i+(24*r)-
1,7+24);rhow*CPw*L*T(i+(24*r)-1,8+24)+P(i+(24*r),1+9)*ho];
     end


a1=D(i+(24*r),1);a2=D(i+(24*r),2);a3=D(i+(24*r),3);a4=D(i+(24*r),4);a5=D(i+(2
4*r),5);a6=D(i+(24*r),6);a7=D(i+(24*r),7);a8=D(i+(24*r),8);a10=D(i+(24*r),10)
;

a11=D(i+(24*r),11);a12=D(i+(24*r),12);a13=D(i+(24*r),13);a14=D(i+(24*r),14);a
15=D(i+(24*r),15);a16=D(i+(24*r),16);a17=D(i+(24*r),17);

a21=D(i+(24*r),21);a22=D(i+(24*r),22);a23=D(i+(24*r),23);a24=D(i+(24*r),24);a
25=D(i+(24*r),25);a26=D(i+(24*r),26);a27=D(i+(24*r),27);

a31=D(i+(24*r),31);a32=D(i+(24*r),32);a33=D(i+(24*r),33);a34=D(i+(24*r),34);a
35=D(i+(24*r),35);a36=D(i+(24*r),36);a37=D(i+(24*r),37);
        a53=D(i+(24*r),53);

K1=K(i+(24*r),1);K2=K(i+(24*r),2);K3=K(i+(24*r),3);K4=K(i+(24*r),4);K5=K(i+(2
4*r),5);
 % Nonlinear optimization
        [x,fval,exitflag,output] = ...
        fmincon(@(x)
myfun(x,D(i+(24*r),1),D(i+(24*r),11),D(i+(24*r),21),D(i+(24*r),31),COP,D(i+(2
4*r),8),D(i+(24*r),10)),xstart,A,b,Aeq,beq,lb,[],...
        @(x)
mycon(x,i+(24*r),D(i+(24*r),2),D(i+(24*r),3),D(i+(24*r),4),D(i+(24*r),5),D(i+
(24*r),6),D(i+(24*r),7),K(i+(24*r),1),D(i+(24*r),12),D(i+(24*r),13),D(i+(24*r
),14),D(i+(24*r),15),D(i+(24*r),16),D(i+(24*r),17),K(i+(24*r),2),D(i+(24*r),2
2),D(i+(24*r),23),D(i+(24*r),24),D(i+(24*r),25),D(i+(24*r),26),D(i+(24*r),27)
,K(i+(24*r),3),D(i+(24*r),32),D(i+(24*r),33),D(i+(24*r),34),D(i+(24*r),35),D(
i+(24*r),36),D(i+(24*r),37),K(i+(24*r),4),hi,D(i+(24*r),53),K(i+(24*r),5),T))
;
        T(i+(24*r),1:38)= [x,fval,exitflag];
 % calculation of building energy consumption based on optimized parameters
        Q1=a4*x(1)+a5*x(2)+a2*x(5)*x(2)+a3*x(5)-a6*x(6)+a7*x(6)*x(5)-hi*x(7)-
K1-0.27*(x(5+8)-x(5))-0.27*(x(5+24)-x(5))-0.27*(x(32+3)-x(5));
        Q2=a14*x(1+8)+a15*x(2+8)+a12*x(5+8)*x(2+8)+a13*x(5+8)-
a16*x(6+8)+a17*x(6+8)*x(5+8)-hi*x(7+8)-K2-0.27*(x(5)-x(5+8))-0.27*(x(5+16)-
x(5+8))-0.27*(x(32+3)-x(5+8));
        Q3=a24*x(1+16)+a25*x(2+16)+a22*x(5+16)*x(2+16)+a23*x(5+16)-
a26*x(6+16)+a27*x(6+16)*x(5+16)-hi*x(7+16)-K3-0.27*(x(5+8)-x(5+16))-
0.27*(x(5+24)-x(5+16))-0.27*(x(32+3)-x(5+16));
```

```
        Q4=a34*x(1+24)+a35*x(2+24)+a32*x(5+24)*x(2+24)+a33*x(5+24)-
a36*x(6+24)+a37*x(6+24)*x(5+24)-hi*x(7+24)-K4-0.27*(x(5)-x(5+24))-
0.27*(x(5+16)-x(5+24))-0.27*(x(32+3)-x(5+24));
        Q5=a4*.68+a53*x(32+3)-a6*x(32+4)+a7*x(32+3)*x(32+4)-K5-0.27*(x(5)-
x(32+3))-0.27*(x(5+8)-x(32+3))-0.27*(x(5+16)-x(32+3))-0.27*(x(5+24)-x(32+3));

        if Q1>0
            y(2)=Q1; y(1)=0;
        else
            y(1)=-Q1; y(2)=0;
        end
        if Q2>0
            y(4)=Q2; y(3)=0;
        else
            y(3)=-Q2; y(4)=0;
        end
        if Q3>0
            y(6)=Q3; y(5)=0;
        else
            y(5)=-Q3; y(6)=0;
        end
        if Q4>0
            y(8)=Q4; y(7)=0;
        else
            y(7)=-Q4; y(8)=0;
        end
        if Q5>0
            y(10)=Q5; y(9)=0;
        else
            y(9)=-Q5; y(10)=0;
        end
% Each zone energy consumption
        ff(i+(24*r)) = 
a1*x(1)+(1/COP+0.25)*y(1)+1.25*y(2)+3*x(6)+a11*x(1+8)+(1/COP+0.25)*y(3)+1.25*
y(4)+3*x(6+8)+a21*x(1+16)+(1/COP+0.25)*y(5)+1.25*y(6)+3*x(6+16)+a31*x(1+24)+(
1/COP+0.25)*y(7)+1.25*y(8)+3*x(6+24)+a1*a10/a8+(1/COP+0.25)*y(9)+1.25*y(10)+3
*x(32+4);
        fh1(i+(24*r))=(1/COP+0.25)*x(3)+1.25*x(4)+3*x(6); fl1(i+(24*r))=
a1*x(1);
        fh2(i+(24*r))=(1/COP+0.25)*x(3+8)+1.25*x(4+8)+3*x(6+8);
fl2(i+(24*r))=a11*x(1+8);

fh3(i+(24*r))=(1/COP+0.25)*x(3+16)+1.25*x(4+16)+3*x(6+16);fl3(i+(24*r))=a21*x
(1+16);

fh4(i+(24*r))=(1/COP+0.25)*x(3+24)+1.25*x(4+24)+3*x(6+24);fl4(i+(24*r))=a31*x
(1+24);

fh5(i+(24*r))=(1/COP+0.25)*x(32+1)+1.25*x(32+2)+3*x(32+4);fl5(i+(24*r))=a10/a
8;

        ET=ET+ff(i+(24*r));

EE=D(i+(24*r),1)*x(1)+D(i+(24*r),11)*x(1+8)+D(i+(24*r),21)*x(1+16)+D(i+(24*r)
,31)*x(1+24)+D(i+(24*r),1)*D(i+(24*r),10)/D(i+(24*r),8)+EE;
        EH=ET-EE;
```

```
    end
end

% Reporting the results
fout1 = fopen('Res1.txt', 'w');
fprintf(fout1, '%8.6f\r\n', EE,EH,ET);
fclose(fout1);

T;
T1=T';
T1(37,1:72)=ff(1:72);
%T2=[T1(1:8,:);fh1;fl1;T1(9:16,:);fh2;fl2;T1(17:24,:);fh3;fl3;T1(25:32,:);fh4
;fl4;T1(33:36,:);fh5;fl5;T1(37:38,:)];
fout = fopen('exp5.txt', 'w');
fprintf(fout, '%8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %12.8f %12.8f %8.6f
%12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f
%12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f %12.8f %8.6f
%12.8f %8.6f %12.8f %8.6f %12.8f\r\n', T1);
fclose(fout);

function f = myfun(x,a1,a11,a21,a31,COP,a8,a10)
         f =
a1*x(1)+(1/COP+0.25)*x(3)+1.25*x(4)+3*x(6)+a11*x(1+8)+(1/COP+0.25)*x(3+8)+1.2
5*x(4+8)+3*x(6+8)+a21*x(1+16)+(1/COP+0.25)*x(3+16)+1.25*x(4+16)+3*x(6+16)+a31
*x(1+24)+(1/COP+0.25)*x(3+24)+1.25*x(4+24)+3*x(6+24)+a1*a10/a8+(1/COP+0.25)*x
(32+1)+1.25*x(32+2)+3*x(32+4);

% Nonlinear constraints
function
[c,ceq]=mycon(x,i,a2,a3,a4,a5,a6,a7,K1,a12,a13,a14,a15,a16,a17,K2,a22,a23,a24
,a25,a26,a27,K3,a32,a33,a34,a35,a36,a37,K4,hi,a53,K5,T)

    if i==1
            ceq=[a4*x(1)+a5*x(2)+x(3)-x(4)+a2*x(5)*x(2)+a3*x(5)-
a6*x(6)+a7*x(6)*x(5)-hi*x(7)-K1-0.27*(x(5+8)-x(5))-0.27*(x(5+24)-x(5))-
0.27*(x(32+3)-x(5))
            a14*x(1+8)+a15*x(2+8)+x(3+8)-x(4+8)+a12*x(5+8)*x(2+8)+a13*x(5+8)-
a16*x(6+8)+a17*x(6+8)*x(5+8)-hi*x(7+8)-K2-0.27*(x(5)-x(5+8))-0.27*(x(5+16)-
x(5+8))-0.27*(x(32+3)-x(5+8))
            a24*x(1+16)+a25*x(2+16)+x(3+16)-
x(4+16)+a22*x(5+16)*x(2+16)+a23*x(5+16)-a26*x(6+16)+a27*x(6+16)*x(5+16)-
hi*x(7+16)-K3-0.27*(x(5+8)-x(5+16))-0.27*(x(5+24)-x(5+16))-0.27*(x(32+3)-
x(5+16))
            a34*x(1+24)+a35*x(2+24)+x(3+24)-
x(4+24)+a32*x(5+24)*x(2+24)+a33*x(5+24)-a36*x(6+24)+a37*x(6+24)*x(5+24)-
hi*x(7+24)-K4-0.27*(x(5)-x(5+24))-0.27*(x(5+16)-x(5+24))-0.27*(x(32+3)-
x(5+24))
            a4*.68+x(32+1)-x(32+2)+a53*x(32+3)-a6*x(32+4)+a7*x(32+3)*x(32+4)-
K5-0.27*(x(5)-x(32+3))-0.27*(x(5+8)-x(32+3))-0.27*(x(5+16)-x(32+3))-
0.27*(x(5+24)-x(32+3))];
    else
```

```
        ceq=[a4*x(1)+a5*x(2)+x(3)-x(4)+a2*x(5)*x(2)+a3*x(5)-
a6*x(6)+a7*x(6)*x(5)-hi*x(7)-K1-0.27*(T(i-1,(5+8))-x(5))-0.27*(T(i-1,(5+24))-
x(5))-0.27*(T(i-1,(32+3))-x(5))
            a14*x(1+8)+a15*x(2+8)+x(3+8)-x(4+8)+a12*x(5+8)*x(2+8)+a13*x(5+8)-
a16*x(6+8)+a17*x(6+8)*x(5+8)-hi*x(7+8)-K2-0.27*(T(i-1,(5))-x(5+8))-0.27*(T(i-
1,(5+16))-x(5+8))-0.27*(T(i-1,(32+3))-x(5+8))
            a24*x(1+16)+a25*x(2+16)+x(3+16)-
x(4+16)+a22*x(5+16)*x(2+16)+a23*x(5+16)-a26*x(6+16)+a27*x(6+16)*x(5+16)-
hi*x(7+16)-K3-0.27*(T(i-1,(5+8))-x(5+16))-0.27*(T(i-1,(5+24))-x(5+16))-
0.27*(T(i-1,(32+3))-x(5+16))
            a34*x(1+24)+a35*x(2+24)+x(3+24)-
x(4+24)+a32*x(5+24)*x(2+24)+a33*x(5+24)-a36*x(6+24)+a37*x(6+24)*x(5+24)-
hi*x(7+24)-K4-0.27*(T(i-1,(5))-x(5+24))-0.27*(T(i-1,(5+16))-x(5+24))-
0.27*(T(i-1,(32+3))-x(5+24))
            a4*.68+x(32+1)-x(32+2)+a53*x(32+3)-a6*x(32+4)+a7*x(32+3)*x(32+4)-
K5-0.27*(T(i-1,(5))-x(32+3))-0.27*(T(i-1,(5+8))-x(32+3))-0.27*(T(i-1,(5+16))-
x(32+3))-0.27*(T(i-1,(5+24))-x(32+3))];
    end
        c=[];
```

Appendix B: DOE-2 program and function for nighttime ventilation modeling

This appendix includes the input file of DOE-2 for modeling five zones building with described HVAC system (DOE-2 sample file). As well as, the nighttime ventilation prediction function (NV-FUN) for controlling working hours of the building fan during the night. Detail description of the function can be found in chapter 5.

```
INPUT LOADS  ..

TITLE    LINE-1 *SIMPLE STRUCTURE RUN, *..
         ABORT           ERRORS     ..
         DIAGNOSTIC        WARNINGS   ..
          RUN-PERIOD
                     JAN 1 2000 THRU DEC 31 2000  ..
$           LOADS-REPORT       VERIFICATION = (ALL-VERIFICATION)
$                        SUMMARY      = (ALL-SUMMARY)  ..
         BUILDING-LOCATION  LATITUDE=45.5  LONGITUDE=73.8
                     ALTITUDE=0
                     TIME-ZONE=5  AZIMUTH=0.0   ..
                $ BUILDING DESCRIPTION

$ STRUCTURE  WOOD FRAME WALLS AND ROOF; 4IN CONCRETE SLAB-ON-GRADE.

$ WALLS      USING CODE-WORDS FROM DOE-2 LIBRARY ( REFERENCE MANUAL PART 2 )
$          STARTING WITH OUTSIDE MATERIAL: WOOD SHINGLES (WD01); PLYWOOD
$          (PW03); R-11 FIBER INSULATION (IN02); AND GYPSUM BOARD (GP01).

$ ROOF       ROOF GRAVEL (RG01), BUILT-UP ROOFING (BR01), R-3 MINERAL BOARD
$          INSULATION (IN22), WOOD SHEATHING CEILING (WD01), AND I-F-R=.76 .

$ SLAB-ON-GRADE EFFECTIVE U-VALUE = .05  (I.E., ASSUMING 4" HEAVY CONCRETE SLAB
$ U-EFF= (U SLAB + AIR FILM) * AREA (1FT PERIMETER)/ TOTAL AREA
$     = 0.8 * 300/5000 = .05
$ WINDOW GLASS:  1/4IN PLATE DOUBLE PANE AND NO INTERNAL SHADING DEVICE.
$ DOOR GLASS:    1/2IN PLATE SINGLE PANE. THERE IS A 10FT WIDE X 4FT DEEP
$            OVERHANG AT THE FRONT DOOR DF-1.
$ INTERIOR LOADS: ADD SURFACE MOUNTED FLUORESCENT LIGHTING AT
$              1.5 WATTS/SQFT.
$              ADD RECEPTACLES FOR EQUIPMENT AT 1 WATT/SQFT.
$              ADD PEOPLE AT 100 SQFT PER PERSON.
$ BUILDING WITH THE ADDITION OF A PLENUM.  THE SPACES ARE ALSO REDEFINED, WITH
$            INTERIOR AND EXTERIOR AREAS SEPARATED BY PARTITIONS WITH
$            A U-VALUE OF 1.5 TO SIMULATE CONVECTIVE HEAT TRANSFER BETWEEN
$            THEM.  INFILTRATION IS ALSO ADDED AT .25 AIR CHANGES/HR.

$ LIGHTING FIXTURES ARE RECESSED FLUORESCENT WITH 20% OF THE HEAT FROM LIGHTING
$            GOING TO THE CEILING PLENUM AND THEREFORE INTO THE RETURN AIR.
```

```
                $ HVAC SYSTEM DESCRIPTION

$ DESIGN TEMPS  COOLING 78F - HEATING 70F.
$ SYSTEM TYPE   A SINGLE VARIABLE AIR VOLUME SYSTEM SERVES THE ENTIRE BUILDING.
$           THE SYSTEM HAS A DRYBULB CONTROLLED ECONOMIZER WITH A LIMIT
$           TEMP OF 65F, VARIABLE SPEED FAN MOTOR, AND VAV BOXES WITH
$           A MINIMUM STOP OF 30%.  THE TEMPERATURE OF THE SUPPLY AIR IS
$           RESET BY OUTSIDE AIR - 60F AT FULL COOLING TO 65F IN WINTER.
$           MINIMUM VENTILATION AIR IS 20 CFM/PERSON.  THE SYSTEM OPERATES
$           FROM 8AM TO 6PM WEEKDAYS AND IS OFF ON WEEKENDS.  THERE IS A
$           NIGHT LOW LIMIT SETPOINT OF 55F TO PREVENT FREEZING. THE FAN IS
$           ALLOWED TO START AT 6AM WHEN NECESSARY FOR BLDG PICK-UP, BUT
$           IS DELAYED AS LONG AS POSSIBLE (I.E., OPTIMUM START).  HEATING
$           AND COOLING ARE NOT ALLOWED TO OPERATE SIMULTANEOUSLY.

$ HVAC PLANT    GAS FIRED HOT WATER GENERATOR  PRESIZED AT .15 MBTUH.
$           RECIPROCATING AIR COOLED CHILLER  PRESIZED AT .18 MBTUH.

$ UTILITIES    NATURAL GAS AT 1.50 DOLLARS PER THERM.
$           ELECTRICITY HAS A TIME-OF-DAY CHARGE AS FOLLOWS:
$                 OFF-PEAK 5 CENTS/KWH  NIGHTS AND WEEKENDS
$                 SHOULDER 6 CENTS/KWH  8AM TO 12 NOON AND FROM
$                                6PM TO 10 PM WEEKDAYS
$                                8AM TO 5PM SATURDAYS
$                 ON-PEAK  7 CENTS/KWH  1PM TO 5PM WEEKDAYS

               $ CONSTRUCTIONS AND GLASS-TYPES

WA-1-2=LAYERS   MATERIAL=(WD01,PW03,IN02,GP01)  ..
RB-1-1=LAYERS   MATERIAL=(RG01,BR01,IN22,WD01)  I-F-R=.76  ..
WALL-1       =CONSTRUCTION      LAYERS=WA-1-2  ..
ROOF-1       =CONSTRUCTION      LAYERS=RB-1-1  ..
CLNG-1       =CONSTRUCTION      U = 0.27  ..          $CEILING
SB-U         =CONSTRUCTION      U = 1.5   ..          $PARTITION
FLOOR-1      =CONSTRUCTION      U = 0.05  ..
W-1          =GLASS-TYPE        GLASS-TYPE-CODE = 3  PANES = 2  ..
DOORS        =GLASS-TYPE        GLASS-TYPE-CODE = 5   ..

               $ OCCUPANCY SCHEDULE

OC-1         =DAY-SCHEDULE      (1,8) (0.0)
                      (9,11) (1.0)
                      (12,14) (0.8,0.4,0.8)
                      (15,18) (1.0)
                      (19,21) (0.5,0.1,0.1)
                      (22,24) (0.0)  ..

OC-2         =DAY-SCHEDULE      (1,24) (0.0)  ..
OC-WEEK      =WEEK-SCHEDULE     (WD) OC-1 (WEH) OC-2  ..
OCCUPY-1     =SCHEDULE          THRU DEC 31 OC-WEEK  ..

               $ LIGHTING SCHEDULE

LT-1         =DAY-SCHEDULE      (1,8) (0.05)
                      (9,14) (0.9,0.95,1.0,0.95,0.8,0.9)
                      (15,18) (1.0)
```

```
                        (19,21) (0.6,0.2,0.2)
                        (22,24) (0.05)  ..

LT-2         =DAY-SCHEDULE      (1,24) (0.05)  ..
LT-WEEK        =WEEK-SCHEDULE      (MON,FRI) LT-1   (WEH) LT-2  ..
LIGHTS-1       =SCHEDULE          THRU DEC 31 LT-WEEK  ..

                 $ OFFICE EQUIPMENT SCHEDULE

EQ-1         =DAY-SCHEDULE      (1,8) (0.02)
                        (9,14) (0.8)
                        (15,20) (0.8,0.7,0.5,0.5,0.3,0.3)
                        (21,24) (0.02)  ..

EQ-2         =DAY-SCHEDULE      (1,24) (0.02)  ..
EQ-WEEK        =WEEK-SCHEDULE      (MON,FRI) EQ-1   (WEH) EQ-2  ..
EQUIP-1       =SCHEDULE          THRU DEC 31 EQ-WEEK  ..

                  $ INFILTRATION SCHEDULE

INFIL-SCH     =SCHEDULE        THRU DEC 31 (ALL) (1,24) (1)  ..
                  $ SET DEFAULT VALUES

             SET-DEFAULT FOR SPACE FLOOR-WEIGHT=100  ..
             SET-DEFAULT FOR WINDOW HEIGHT=4.0 GLASS-TYPE=W-1  Y=3  ..

                  $ GENERAL SPACE DEFINITION

OFFICE        =SPACE-CONDITIONS
                        PEOPLE-SCHEDULE      =OCCUPY-1
                        NUMBER-OF-PEOPLE     =50
                        PEOPLE-HEAT-GAIN     =400
                        LIGHTING-SCHEDULE    =LIGHTS-1
                        LIGHTING-TYPE        =REC-FLUOR-RV
                        LIGHT-TO-SPACE       =.80
                        LIGHTING-W/SQFT      =1.5
                        EQUIP-SCHEDULE       =EQUIP-1
                        EQUIPMENT-W/SQFT     =1
                        INF-METHOD           =AIR-CHANGE
                        AIR-CHANGES/HR       =0.25
                        INF-SCHEDULE         =INFIL-SCH  ..

                  $ SPECIFIC SPACE DETAILS

PLENUM-1      =SPACE            ZONE-TYPE=PLENUM
                        VOLUME=10000         FLOOR-WEIGHT=5
                        AREA=5000            Z=8  ..
   WALL-1PF   =EXTERIOR-WALL     HEIGHT = 2          WIDTH = 100
                        AZIMUTH = 180
                        CONSTRUCTION = WALL-1   ..
   WALL-1PR   =EXTERIOR-WALL     HEIGHT = 2          WIDTH =  50
                        AZIMUTH =  90        X = 100
                        CONSTRUCTION = WALL-1   ..
   WALL-1PB   =EXTERIOR-WALL     HEIGHT = 2          WIDTH = 100
                        AZIMUTH = 0          X = 100
                        Y = 50
```

```
                        CONSTRUCTION = WALL-1   ..
   WALL-1PL   =EXTERIOR-WALL     HEIGHT = 2           WIDTH =  50
                        AZIMUTH = 270        Y = 50
                        CONSTRUCTION = WALL-1   ..
   TOP-1      =ROOF             HEIGHT=50           WIDTH=100
                        X=0   Y=0   Z=2      AZIMUTH = 180
                        TILT=0              GND-REFLECTANCE=0
                        CONSTRUCTION = ROOF-1   ..
SPACE1-1      =SPACE            SPACE-CONDITIONS = OFFICE
                        AREA = 1056         VOLUME = 8448
                        NUMBER-OF-PEOPLE = 11   ..
   FRONT-1    =EXTERIOR-WALL     HEIGHT = 8           WIDTH = 100
                        X=0   Y=0   Z=0      AZIMUTH = 180
                        CONSTRUCTION = WALL-1   ..
     WF-1     =WINDOW           WIDTH = 45           X = 10  ..
     DF-1     =WINDOW           WIDTH = 8            HEIGHT = 8
                        X = 70              Y = 0
                        GLASS-TYPE = DOORS
                        OVERHANG-A=1        OVERHANG-B=.5
                        OVERHANG-W=10       OVERHANG-D=4  ..
   C1-1       =INTERIOR-WALL     AREA = 1056         NEXT-TO  PLENUM-1
                        CONSTRUCTION = CLNG-1   ..
   F1-1       =UNDERGROUND-FLOOR  AREA = 1056
                        CONSTRUCTION = FLOOR-1   ..
   SB12       =INTERIOR-WALL     AREA = 135.76       NEXT-TO  SPACE2-1
                        CONSTRUCTION = SB-U   ..
   SB14       =INTERIOR-WALL     LIKE SB12           NEXT-TO  SPACE4-1   ..
   SB15       =INTERIOR-WALL     AREA = 608          NEXT-TO  SPACE5-1
                        CONSTRUCTION = SB-U   ..
SPACE2-1      =SPACE            SPACE-CONDITIONS = OFFICE
                        AREA  = 456         VOLUME = 3648
                        NUMBER-OF-PEOPLE =  5   ..
   RIGHT-1    =EXTERIOR-WALL     HEIGHT = 8           WIDTH =  50
                        X=100  Y=0   Z=0     AZIMUTH =  90
                        CONSTRUCTION = WALL-1   ..
     WR-1     =WINDOW           WIDTH = 25           X = 12.5  ..
   C2-1       =INTERIOR-WALL     AREA =  456         NEXT-TO  PLENUM-1
                        CONSTRUCTION = CLNG-1   ..
   F2-1       =UNDERGROUND-FLOOR  AREA = 456
                        CONSTRUCTION = FLOOR-1   ..
   SB23       =INTERIOR-WALL     AREA = 135.76       NEXT-TO  SPACE3-1
                        CONSTRUCTION = SB-U   ..
   SB25       =INTERIOR-WALL     AREA = 208          NEXT-TO  SPACE5-1
                        CONSTRUCTION = SB-U   ..
SPACE3-1      =SPACE            SPACE-CONDITIONS = OFFICE
                        AREA =   1056       VOLUME = 8448
                        NUMBER-OF-PEOPLE   =  11   ..
   BACK-1     =EXTERIOR-WALL     HEIGHT = 8           WIDTH = 100
                        X=100  Y=50  Z=0     AZIMUTH =   0
                        CONSTRUCTION = WALL-1   ..
     WB-1     =WINDOW           WIDTH = 45           X = 10  ..
     DB-1     =WINDOW           WIDTH = 7            HEIGHT = 7
                        X = 70              Y = 0
                        GLASS-TYPE=DOORS   ..
   C3-1       =INTERIOR-WALL     AREA = 1056         NEXT-TO  PLENUM-1
                        CONSTRUCTION = CLNG-1   ..
```

```
   F3-1      =UNDERGROUND-FLOOR  AREA = 1056
                    CONSTRUCTION = FLOOR-1   ..
   SB34      =INTERIOR-WALL     AREA = 135.8        NEXT-TO  SPACE4-1
                    CONSTRUCTION = SB-U   ..
   SB35      =INTERIOR-WALL     AREA = 608          NEXT-TO  SPACE5-1
                    CONSTRUCTION = SB-U   ..
SPACE4-1      =SPACE            SPACE-CONDITIONS = OFFICE
                    AREA = 456          VOLUME = 3648
                    NUMBER-OF-PEOPLE   =  5   ..
   LEFT-1    =EXTERIOR-WALL     HEIGHT = 8          WIDTH = 50
                    X=0   Y=50  Z=0      AZIMUTH = 270
                    CONSTRUCTION = WALL-1   ..
    WL-1     =WINDOW            WIDTH = 25          X = 12.5  ..
   C4-1      =INTERIOR-WALL     AREA =  456         NEXT-TO  PLENUM-1
                    CONSTRUCTION = CLNG-1   ..
   F4-1      =UNDERGROUND-FLOOR  AREA = 456
                    CONSTRUCTION = FLOOR-1  ..
   SB45      =INTERIOR-WALL     AREA = 208          NEXT-TO  SPACE5-1
                    CONSTRUCTION = SB-U   ..
SPACE5-1      =SPACE            SPACE-CONDITIONS = OFFICE
                    AREA =   1976       VOLUME =15808
                    NUMBER-OF-PEOPLE   =  20   ..
   C5-1      =INTERIOR-WALL     AREA = 1976         NEXT-TO  PLENUM-1
                    CONSTRUCTION = CLNG-1   ..
   F5-1      =UNDERGROUND-FLOOR  AREA = 1976
                    CONSTRUCTION = FLOOR-1   ..

              $ LOADS HOURLY REPORT

  HR-SCH-1    =SCHEDULE       THRU AUG 4  (ALL)(1,24)(0)
                   THRU AUG 5  (ALL)(1,24)(0)
                   THRU DEC 31 (ALL)(1,24)(0) ..

   LRB-1     =REPORT-BLOCK      VARIABLE-TYPE=GLOBAL
          VARIABLE-LIST=(4,17,15) .. $ dbt, wind speed, hor. solar $

   LRB-2     =REPORT-BLOCK      VARIABLE-TYPE=BUILDING
          VARIABLE-LIST=(19) .. $ building cooling load $

   LDS-REP-1  =HOURLY-REPORT     REPORT-SCHEDULE=HR-SCH-1
          REPORT-BLOCK=(LRB-1,LRB-2) ..

END  ..
COMPUTE LOADS   ..
INPUT SYSTEMS   ..

          SYSTEMS-REPORT  SUMMARY=(ALL-SUMMARY)  ..

          SUBR-FUNCTIONS

                VARVOL-1Z=*SAVETEMP*
                DAYCLS-3=*NV-FUN*
                 ..

          $ SYSTEMS SCHEDULES
```

```
FAN-1         =DAY-SCHEDULE      (1,8)(0)(9,18)(1)(19,24)(-1)  ..
FAN-2         =DAY-SCHEDULE      (1,24)(0)   ..
FAN-3         =DAY-SCHEDULE      (1,8)(0)(9,18)(1) (19,24)(-1) ..
FAN-SCHED     =SCHEDULE
                                         THRU MAY 31 (WD) FAN-1 (WEH) FAN-2
                        THRU AUG 31 (WD) FAN-1 (WEH) FAN-2
                        THRU DEC 31 (WD) FAN-1 (WEH) FAN-2  ..

N_FAN-1         =DAY-SCHEDULE     (1,8)(1)(9,21)(0)(22,24)(0)  ..
N_FAN-2         =DAY-SCHEDULE      (1,24) (0)   ..

N_FAN-SCHED     =SCHEDULE
                                         THRU MAY 31 (WD) N_FAN-2 (WEH) N_FAN-2
                        THRU AUG 31 (WD) N_FAN-1 (WEH) N_FAN-2
                        THRU DEC 31 (WD) N_FAN-2 (WEH) N_FAN-2  ..

N_TEMP-1         =DAY-SCHEDULE    (1,8)(65)(9,21)(99)(22,24)(99)..
N_TEMP-2         =DAY-SCHEDULE      (1,24) (99)   ..

N_TEMP-SCHED     =SCHEDULE
                                         THRU MAY 31 (WD) N_TEMP-2 (WEH) N_TEMP-2
                        THRU AUG 31 (WD) N_TEMP-1 (WEH) N_TEMP-2
                        THRU DEC 31 (WD) N_TEMP-2 (WEH) N_TEMP-2  ..

HEAT-1      =DAY-SCHEDULE    (1,8) (55)   (9,18) (70)  (19,24) (55)  ..
HEAT-2      =DAY-SCHEDULE    (1,24) (55)   ..
HEAT-WEEK   =WEEK-SCHEDULE   (MON,FRI)  HEAT-1   (WEH)  HEAT-2   ..
HEAT-SCHED  =SCHEDULE        THRU DEC 31   HEAT-WEEK   ..


COOLOFF    =SCHEDULE       THRU DEC 31 (ALL) (1,8)(0)(9,24)(60) ..
HEATOFF    =SCHEDULE       THRU DEC 31 (ALL) (1,8)(0)(9,24)(60)  ..

COOL-1      =DAY-SCHEDULE    (1,8)(99)(9,18)(78)(19,24)(99)  ..
COOL-2      =DAY-SCHEDULE    (1,24) (99)   ..
COOL-WEEK   =WEEK-SCHEDULE   (MON,FRI)  COOL-1   (WEH)  COOL-2   ..
COOL-SCHED  =SCHEDULE        THRU DEC 31   COOL-WEEK   ..

R1 DAY-RESET-SCH  SUPPLY-HI 65  SUPPLY-LO 60
             OUTSIDE-LO 30  OUTSIDE-HI 75  ..
SAT-RESET RESET-SCHEDULE  THRU DEC 31 (ALL) R1  ..


              $ SYSTEM DESCRIPTION

ZAIR        =ZONE-AIR      OA-CFM/PER=20  ..

 CONTROL     =ZONE-CONTROL  DESIGN-HEAT-T=70  DESIGN-COOL-T=76
                   HEAT-TEMP-SCH= HEAT-SCHED
                   COOL-TEMP-SCH= COOL-SCHED
                   THERMOSTAT-TYPE=REVERSE-ACTION  ..

SPACE1-1     =ZONE         ZONE-AIR=ZAIR  SIZING-OPTION= ADJUST-LOADS
                   ZONE-CONTROL=CONTROL ..
SPACE2-1     =ZONE         LIKE SPACE1-1   ..
```

```
SPACE3-1    =ZONE        LIKE SPACE1-1   ..
SPACE4-1    =ZONE        LIKE SPACE1-1   ..
SPACE5-1    =ZONE        LIKE SPACE1-1  ..

PLENUM-1    =ZONE        ZONE-TYPE=PLENUM  SIZING-OPTION= ADJUST-LOADS
                  DESIGN-HEAT-T=50  DESIGN-COOL-T=95  ..

S-CONT      =SYSTEM-CONTROL  COOLING-SCHEDULE= COOLOFF
                   HEATING-SCHEDULE= HEATOFF
                   HEAT-SET-T=65
                   COOL-CONTROL=RESET
                   COOL-RESET-SCH=SAT-RESET
                   MIN-SUPPLY-T=60 ..

S-AIR       =SYSTEM-AIR     OA-CONTROL=TEMP ..

S-FAN       =SYSTEM-FANS    FAN-SCHEDULE=FAN-SCHED  FAN-CONTROL=SPEED
                   SUPPLY-STATIC=5.5  SUPPLY-EFF=.7     ..

S-TERM      =SYSTEM-TERMINAL REHEAT-DELTA-T=58
                   MIN-CFM-RATIO=0.3   ..

SYST-1      =SYSTEM        SYSTEM-TYPE=VAVS
                   SYSTEM-CONTROL= S-CONT
                   SYSTEM-FANS= S-FAN
                   SYSTEM-TERMINAL= S-TERM
                            SYSTEM-AIR=S-AIR
                   ECONO-LIMIT-T=65

                            NIGHT-VENT-CTRL= SCHEDULED+DEMAND
                            NIGHT-VENT-SCH= N_FAN-SCHED
                            NIGHT-VENT-DT= 5
                            NIGHT-VENT-RATIOS= (0.63,0.7,0.63,0,0,0)
                            VENT-TEMP-SCH= N_TEMP-SCHED


                   RETURN-AIR-PATH=PLENUM-ZONES
                   PLENUM-NAMES=(PLENUM-1)
                   ZONE-NAMES=(SPACE1-1,SPACE5-1,SPACE2-1
                        SPACE3-1,SPACE4-1,PLENUM-1)

$                           FUNCTION=(*H-NV-FON-FUNBFSYS4*,*none*)   ..

          $ SYSTEMS HOURLY REPORT

 HR-SCH-2    =SCHEDULE      THRU AUG 4  (ALL)(1,24)(1)
                   THRU AUG 5  (ALL)(1,24)(1)
                   THRU DEC 31 (ALL)(1,24)(1) ..

  SRB-1     =REPORT-BLOCK      VARIABLE-TYPE=GLOBAL
        VARIABLE-LIST=(8) .. $ outside dbt, wbt $

  SRB-2     =REPORT-BLOCK      VARIABLE-TYPE=SPACE1-1
        VARIABLE-LIST=(7) .. $ thermostat setpoint,
                        $ zone temp, extraction rate
  SRB-4     =REPORT-BLOCK      VARIABLE-TYPE=SPACE5-1
```

```
            VARIABLE-LIST=(6) .. $ thermostat setpoint,
                              $ zone temp, extraction rate

   SRB-3      =REPORT-BLOCK       VARIABLE-TYPE=SYST-1
            VARIABLE-LIST=(5,6,17,23,33,32,39,25) .. $ coil leaving air temp,
                              $ return air temp, coil load.

   SYSS-REP-1 =HOURLY-REPORT      REPORT-SCHEDULE=HR-SCH-2
            REPORT-BLOCK=(SRB-1,SRB-2,SRB-4,SRB-3) ..

END   ..

##INCLUDE NV- FUN.inc
 ED NV- FUN.inc


COMPUTE SYSTEMS   ..

INPUT PLANT   ..

           PLANT-REPORT  SUMMARY=(ALL-SUMMARY)
                 VERIFICATION = (ALL-VERIFICATION)  ..

            $ HOT-WATER GENERATOR

HWG     =PLANT-EQUIPMENT  TYPE=HW-BOILER  SIZE=-999  ..
 PLANT-PARAMETERS  HERM-REC-COND-TYPE=AIR  ..

            $ AIR-COOLED RECIPROCATING CHILLER

CHIL1      =PLANT-EQUIPMENT  TYPE=HERM-REC-CHLR  SIZE=-999 ..

 PLANT-COSTS      PROJECT-LIFE=25  DISCOUNT-RATE=5  ..
 ENERGY-RESOURCE  RESOURCE=ELECTRICITY  ..
 ENERGY-RESOURCE  RESOURCE=NATURAL-GAS  ENERGY/UNIT=100000
             UNIT-NAME=THERMS   ..

            $ PLANT HOURLY REPORT

   HR-SCH-3   =SCHEDULE       THRU AUG 4  (ALL)(1,24)(0)
                   THRU AUG 5  (ALL)(1,24)(0)
                   THRU DEC 31 (ALL)(1,24)(0) ..

   PRB-1      =REPORT-BLOCK       VARIABLE-TYPE=END-USE
            VARIABLE-LIST=(6) .. $ chiller load,
                               $ part load ratio, EIR
   PLT-REP-1  =HOURLY-REPORT   REPORT-SCHEDULE=HR-SCH-3
            REPORT-BLOCK=(PRB-1) ..

END  ..
COMPUTE PLANT   ..

INPUT ECONOMICS  ..
DIAGNOSTIC WARNINGS ..
ECONOMICS-REPORT  SUMMARY (ALL-SUMMARY)  ..
```

```
BELOW-50KW  = UTILITY-RATE
            RESOURCE=ELECTRICITY
            DEMAND-QUALS = (0,50)
            USE-MIN-qUALS = NO
            QUALIFY-RATE = ALL-MONTHS
            BLOCK-CHARGES = (SMALL-BLOCK)..

SMALL-BLOCK = BLOCK-CHARGE
            BLOCK1-TYPE = ENERGY
            BLOCK1-DATA = (900 0.0539
                         1  0.0751) ..

ABELOW-50KW  = UTILITY-RATE
             RESOURCE=ELECTRICITY
             DEMAND-QUALS = (50,0)
             USE-MIN-qUALS = NO
             BLOCK-CHARGES= (WINTER-BLK, SUMMER-BLK) ..


    WINTER-BLK= BLOCK-CHARGE
              BLOCK-SCH=SEASONS-SCH
              SCH-FLAG=1
              BLOCK1-TYPE=DEMAND
              BLOCK1-DATA= (1,6.21) ..

    SUMMER-BLK= BLOCK-CHARGE
              BLOCK-SCH=SEASONS-SCH
              SCH-FLAG=2
              BLOCK1-TYPE=DEMAND
              BLOCK1-DATA= (1,1.26) ..

   SEASONS-SCH=SCHEDULE THRU MAR 31 (ALL) (1,24) (1)
                  THRU NOV 30 (ALL) (1,24) (2)
                  THRU DEC 31 (ALL) (1,24) (1) ..

 GAS-COST   = UTILITY-RATE   RESOURCE = NATURAL-GAS
                        ENERGY-CHG = .60  ..
END  ..
COMPUTE ECONOMICS  ..
          STOP ..
```

Function

```
FUNCTION NAME NV–FUN  ..

ASSIGN MON=IMO        DAY=IDAY       HR=IHR
      INILZE=INILZE
      TOUT=DBT
      HEATON=HON     COOLON=CON
      FONX=FON
      POX=PO
      CFMX=CFM
      QCX=QC
      QHX=QH
      TSPACE=XXX10
      W_H_DAY=ISCDAY
```

```
      ..

      CALCULATE ..

C  FOR ADDING CONSTRAINTS OF INDOOR AND OUTDOOR TEMPERATURE DIFFERENCE
C       IF (TOUT+5.GT.TSPACE) GOTO 1010

        IF (MON.EQ.6.OR.MON.EQ.7.OR.MON.EQ.8) GOTO 1010
        IF (HR.EQ.24) FONX=0
        TPAV=(TP_OUTMAX+TP_OUTMIN)/2

       IF(TPAV.LT.61) GOTO 1020
       IF(TPAV.LT.63) GOTO 1030
       IF(TPAV.GE.63) GOTO 1010

1020   CONTINUE
       IF (MON.LE.3.AND.HR.LE.8) FONX=0
       IF (MON.GE.11.AND.HR.LE.8) FONX=0
       IF (MON.GE.4.AND.MON.LE.10.AND.HR.LE.7) FONX=0
       IF (HR.EQ.24) FONX=0

1030   CONTINUE
       IF (MON.LE.3.AND.HR.LE.3) FONX=0
       IF (MON.GE.11.AND.HR.LE.3) FONX=0
       IF (MON.GE.4.AND.MON.LE.10.AND.HR.LE.3) FONX=0
       IF (HR.EQ.24) FONX=0

1010   CONTINUE
       IF (HR.EQ.1) TOUT_MIN = TOUT
       IF (HR.EQ.1) TOUT_MAX = TOUT
       IF(TOUT_MIN.GE.TOUT)TOUT_MIN=TOUT
       IF(TOUT_MAX.LE.TOUT)TOUT_MAX=TOUT
       IF(HR.EQ.20)TOUT20=TOUT
       IF(HR.EQ.21)TOUT21=TOUT
       IF(HR.EQ.21)TTREND=TOUT-TOUT21PRE
       IF(HR.EQ.21)TOUT21PRE=TOUT
       IF(HR.EQ.22)TDROP=TOUT20-TOUT


       IF(HR.LT.24) GO TO 1040
C   Calculate Vent Temperature at Hour 24
        TOUT24=TOUT
        TIN24=TSPACE
        TP_OUTMIN=0.659*TOUT_MIN+0.307*TOUT24-0.184*TDROP
        TP_OUTMAX=TOUT_MAX+0.349*TTREND-0.1*TDROP
        IF (HR.EQ.24) NV_ON =0
        IF((TP_OUTMAX+TP_OUTMIN)/2.GT.63) NV_ON =1

1040   CONTINUE
        FON=FONX

       PRINT 51,MON,DAY,HR,TP_OUTMIN,TP_OUTMAX,FONX,POX,NV_ON,TOUT
51      FORMAT(' ',3F5.0,F7.1,F7.1, F7.0,F20.10,F8.2,F8.2)

C                    IF (INILZE.LT.8) RETURN
       END
```

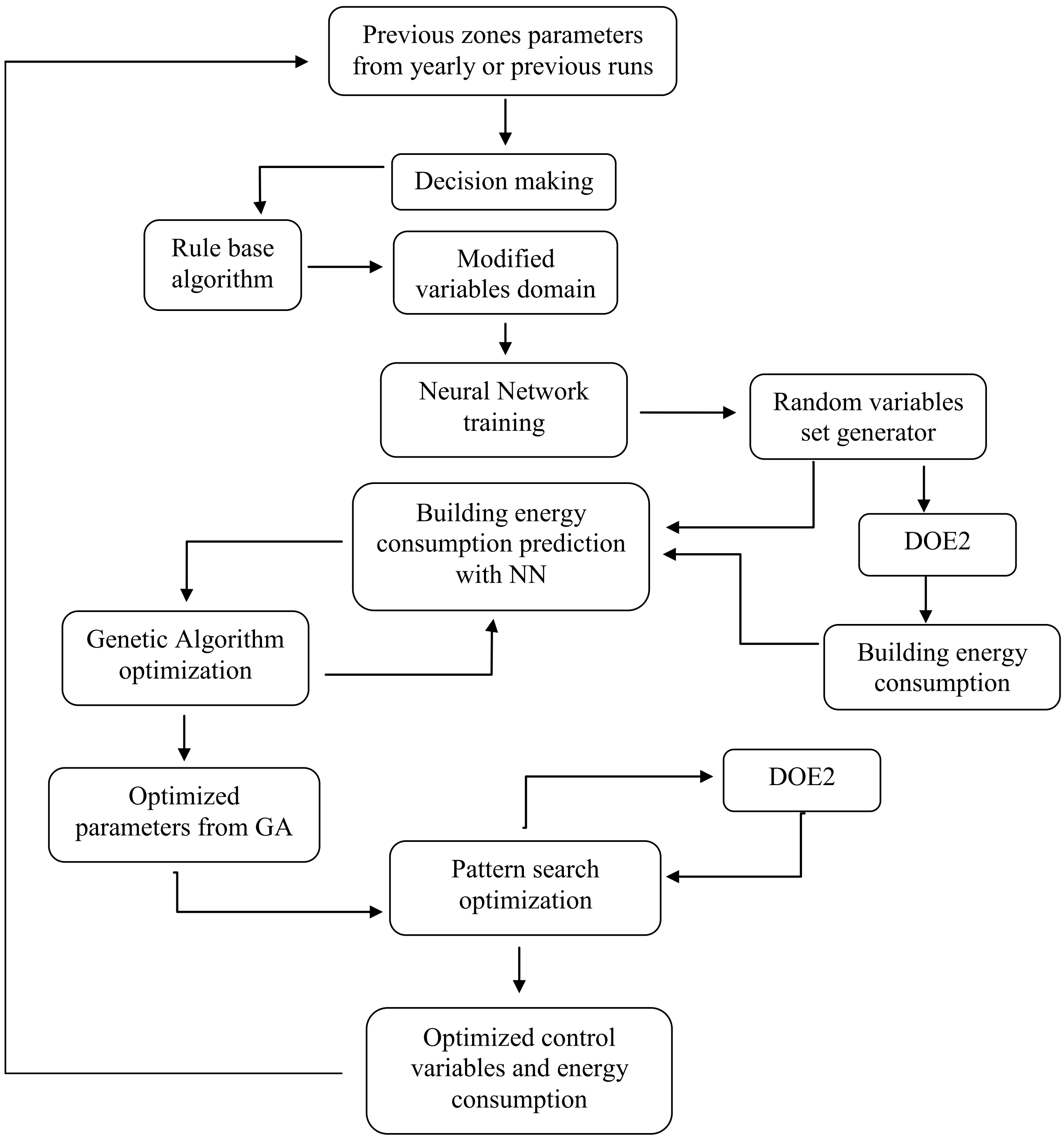
```
      END-FUNCTION ..

      FUNCTION NAME=SAVETEMP ..
 $
 $ saves last hours zone temps for next hour's heat load calculations
 $
ASSIGN MON=IMO DAY=IDAY HR=IHR TNOW=TNOW
           FONX=FON
     TSPACE=XXX10 DBT=DBT  NZ=NZ HUMRAT=HUMRAT ..
     CALCULATE ..

    IF (NZ.LT.1) GO TO 100
    IF (NZ.EQ.1) GO TO 40
    IF (NZ.GE.2) GO TO 100
 40  TSPACE=TNOW
100  CONTINUE
    END
    END-FUNCTION ..
```

Appendix C: DOE-2 and MATLAB integrated program

In this section MATLAB program to connect DOE-2 and genetic algorithm for current hour integrated building optimization by using decision making and pattern search algorithm is presented.



```
function RT_OPT_GA_NonDyn_PS

clc
clear all

global ELE
global IT
Month=8
Months='Aug'
Day=int32(18)
Hr=int32(11)
Dur=4
IT=0;
% replacing zone temp for first hours of day from yearly simulation
%**************
     foutD = fopen('c:\doe21e\Date.txt', 'w');
     fprintf(foutD, 'Date %2.0f %2.0f %2.0f \n', Hr,Day,Month);
     fclose(foutD);

     [s,r] = system('read-HR-T.bat');
     fhrt = fopen('c:\doe21e\ZONETEMP.txt');
     T = fscanf(fhrt, '%g %g', [6 inf]);
     fclose(fhrt);
     T=T';

    foutT = fopen('c:\doe21e\OUTMAT-T.txt', 'w');
    fprintf(foutT, '$ 10002 %1.0f %1.0f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f\n', ...
    Day,Month,T(1,1),T(1,2),T(1,3),T(1,4),T(1,5),T(1,6),...
    T(2,1),T(2,2),T(2,3),T(2,4),T(2,5),T(2,6));
    fclose(foutT);
    [s,r] = system('readreplaceRT-Z-Temp.bat');

%***************

    % previous hours optimized variables will be stored in PrHr matrice to
apply in DOE2 file (From hour 9 to 18 of working hours)
     PrHr1=[0 0 0 0 50 70 78 70 78 70 78 70 78 70 78];
     PrHr=[PrHr1;PrHr1;PrHr1;PrHr1;PrHr1;PrHr1;PrHr1;PrHr1;PrHr1;PrHr1];
    %********
    % generating data for NN training
    % Working hour period (Hr must be higher than 8)
    for i=Hr:(Dur+Hr)

% fuzzy logic

     foutF = fopen('c:\doe21e\DateFu.txt', 'w');
     fprintf(foutF, 'Date %2.0f %2.0f %2.0f \n', i,Day,Month);
     fclose(foutF);


   [s,r] = system('fuzzyrulesvariables.bat');
    foutV = fopen('c:\doe21e\var-domain.txt', 'w');
    fprintf(foutT, '$ 10002 %1.0f %1.0f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f\n', ...
```

```
      Vu1,Vu2,Vu3,Vu4,Vu5,Vu6,Vu7,Vu8,Vu9,Vu10,Vl1,Vl2,Vl3,Vl4,Vl5,Vl6,Vl7,Vl
      8,Vl9,Vl10);
    fclose(foutV);


    % optimization variables limit
        nvars=10;
%   without fuzzy modification
%        ub=[1,1,1,1,300,77.5,77.5,77.5,77.5,77.5];
%        lb=[0,0,0,0,50,70,70,70,70,70];

%   with fuzzy modification
        ub=[Vu1,Vu2,Vu3,Vu4,Vu5,Vu6,Vu7,Vu8,Vu9,Vu10];
        lb=[Vl1,Vl2,Vl3,Vl4,Vl5,Vl6,Vl7,Vl8,Vl9,Vl10];

        options = gaoptimset('Generations',2,'PopulationSize',50);
        options = gaoptimset(options,'PlotFcns',@gaplotbestf);

        fop= @(x) myfun(x,i,ELE,Months,Day,PrHr);
        [x,fval,exitflag] = ga(fop,nvars,[],[],[],[],lb,ub,[],options);


% generating required results for using in NN based on previous results
   % building energy consumption

EC(1:IT)=(ELE(:,11)+ELE(:,12)+ELE(:,13)+ELE(:,14)+ELE(:,15)+ELE(:,16)+ELE(:,1
7)/(3*3412.14));
   % total res
        resNN=[ELE(:,1:10),EC'];

        ROW_DATAS = resNN;
%        ROW_DATAS=ROW_DATAS';
        INP=ROW_DATAS(:,1:10);
        OUT=ROW_DATAS(:,11);

        ptr=(INP(1:IT,:))'; ttr=(OUT(1:IT,:))';

            numHiddenNeurons = 30;  % Adjust as desired
            net1 = newfit(ptr,ttr,numHiddenNeurons);
            net1.divideParam.trainRatio = 70/100;  % Adjust as desired
            net1.divideParam.valRatio = 15/100;  % Adjust as desired
            net1.divideParam.testRatio = 15/100;  % Adjust as desired

            net1.trainParam.goal=1e-15;
            net1.performParam=1e-15;
            net1.adaptParam=1e-15;

% Train and Apply Network
            [net1,tr] = train(net1,ptr,ttr);

% optimization based on trained NN
        option = gaoptimset('Generations',20,'PopulationSize',100);
        option = gaoptimset(option,'PlotFcns',@gaplotbestf);
```

```
        fp= @(x) opfun(x,net1,PrHr,i);
        [x,fval,exitflag] = ga(fp,nvars,[],[],[],[],lb,ub,[],option);


%   Applying local search

      x0=x;
      %****

ubps=[min(x(1)+0.1,1),min(x(2)+0.1,1),min(x(3)+0.1,1),min(x(4)+0.1,1),min(x(5
)+10,300),min(x(6)+0.5,77.5),min(x(7)+0.5,77.5),min(x(8)+0.5,77.5),min(x(9)+0
.5,77.5),min(x(10)+0.5,77.5)];
      lbps=[max(x(1)-0.1,0),max(x(2)-0.1,0),max(x(3)-0.1,0),max(x(4)-
0.1,0),max(x(5)-10,50),max(x(6)-0.5,70),max(x(7)-0.5,70),max(x(8)-
0.5,70),max(x(9)-0.5,70),max(x(10)-0.5,70)];

      optionps = psoptimset('MaxIter',100);

      PS= @(x) myfun(x,i,ELE,Months,Day,PrHr);
      [x,fval,exitflag] = patternsearch(PS,x0,[],[],[],[],lbps,ubps);

% finding energy consumption based on optimization result
% y2 and y3 can be used in multi hour optimization
%*************************
    y1=[x(1) x(2) x(3) x(4) x(5) x(6) x(6)+0.5 x(7) x(7)+0.5 x(8) x(8)+0.5
x(9) x(9)+0.5 x(10) x(10)+0.5];
%    y2=[x(11) x(12) x(13) x(14) x(5) x(15) x(15)+0.5 x(16) x(16)+0.5 x(17)
x(17)+0.5 x(18) x(18)+0.5 x(19) x(19)+0.5];
%    y3=[x(20) x(21) x(22) x(23) x(5) x(24) x(24)+0.5 x(25) x(25)+0.5 x(26)
x(26)+0.5 x(27) x(27)+0.5 x(28) x(28)+0.5];
    y=PrHr;
    y((i-8),:)=y1;



%    y((i-8)+1,:)=y2;
%    y((i-8)+2,:)=y3;



    PrHr((i-8),:)=y1;

    for j=1:10
        R(j,:)={1000+j,Months,Day,i,(1-0.75*y(j,1)),(1-0.80*y(j,1)),(1-
0.35*y(j,1)),(1-0.75*y(j,2)),(1-0.80*y(j,2)),(1-0.35*y(j,2)),(1-
0.75*y(j,3)),(1-0.80*y(j,3)),(1-0.35*y(j,3)),(1-0.75*y(j,4)),(1-
0.80*y(j,4)),(1-
0.35*y(j,4)),y(j,5),y(j,6),y(j,7),y(j,8),y(j,9),y(j,10),y(j,11),y(j,12),y(j,1
3),y(j,14),y(j,15)};
    end

   fout = fopen('c:\doe21e\OUTMAT.txt', 'w');
    for row=1:10
        fprintf(fout,...
```

```
    '$ %4.0f %s %1.0f %1.0f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f\r\n',R{row,:});
    end
    fclose(fout);
    [s,r] = system('readreplaceRT1-Tot-Dyn-Res-PrHr.bat');

    [s,r] = system('readRT1-F-Tot-Res.bat');

    fF = fopen('c:\doe21e\FRes.txt');
    P = fscanf(fF, '%g %g', [7 inf]);
    fclose(fF);
    P=P';

    RE((i-Hr)+1,1:10)=x(1:10);
    P1((i-Hr)+1,1:17)=[RE((i-
Hr)+1,1:10),P(1,1),P(1,2),P(1,3),P(1,4),P(1,5),P(1,6),P(1,7)];
    end
        fres = fopen('c:\doe21e\resOPT.txt', 'w');
        fprintf(fres,'%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f\r\n', P1');
        fclose(fres);

%*************************



function f = myfun(x,i,ELE,Months,Day,PrHr)
global ELE
global IT

IT=IT+1;

% modifying PrHr by each of GA population to apply in DOE2 for finding each
of population energy consumption
% y2 and y3 can be used in multi hour optimization
    y=PrHr;
    y1=[x(1) x(2) x(3) x(4) x(5) x(6) x(6)+0.5 x(7) x(7)+0.5 x(8) x(8)+0.5
x(9) x(9)+0.5 x(10) x(10)+0.5];
%    y2=[x(11) x(12) x(13) x(14) x(5) x(15) x(15)+0.5 x(16) x(16)+0.5 x(17)
x(17)+0.5 x(18) x(18)+0.5 x(19) x(19)+0.5];
%    y3=[x(20) x(21) x(22) x(23) x(5) x(24) x(24)+0.5 x(25) x(25)+0.5 x(26)
x(26)+0.5 x(27) x(27)+0.5 x(28) x(28)+0.5];

    y((i-8),:)=y1;
%    y((i-8)+1,:)=y2;
%    y((i-8)+2,:)=y3;

 % generate and store all required variables in OUTMAT
    for j=1:10
    R(j,:)={1000+j,Months,Day,i,(1-0.75*y(j,1)),(1-0.80*y(j,1)),(1-
0.35*y(j,1)),(1-0.75*y(j,2)),(1-0.80*y(j,2)),(1-0.35*y(j,2)),(1-
0.75*y(j,3)),(1-0.80*y(j,3)),(1-0.35*y(j,3)),(1-0.75*y(j,4)),(1-
0.80*y(j,4)),(1-
```

```
0.35*y(j,4)),y(j,5),y(j,6),y(j,7),y(j,8),y(j,9),y(j,10),y(j,11),y(j,12),y(j,1
3),y(j,14),y(j,15)};
    end

   fout = fopen('c:\doe21e\OUTMAT.txt', 'w');
 for row=1:10
    fprintf(fout,...
    '$ %4.0f %s %1.0f %1.0f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f %8.2f
%8.2f %8.2f\r\n',R{row,:});
 end
    fclose(fout);

 % Create DOE2 file and run it
    [s,r] = system('readreplaceRT1-Tot-nonDyn-Run-PrHr1.bat');

 %read the results of energy consumption from DOE2 file
    [s,r] = system('readRT1-F-Tot-Run.bat');

    fF = fopen('c:\doe21e\FRun.txt');
    P = fscanf(fF, '%g %g', [7 inf]);
    fclose(fF);

%    res=[R(1),R(2),R(3),R(4),R(5),R(6),R(7),R(8)];
    P=P';
    ELE(IT,1:17)=[x(1:10),P(1,:)];
    f=(P(1,1)+P(1,2)+P(1,3)+P(1,4)+P(1,5)+P(1,6)+P(1,7)/(3*3412.14))


function fo = opfun(x,net1,PrHr,i)

% generating required variables for using in NN based on x
% energy consumption for hour i

   inNN1=[x(1:10)];
   outputs1 = sim(net1,inNN1');
   fo=outputs1;
```