Simplified Predictive Control for Load Management: A Self-Learning Approach Applied to Electrically Heated Floor

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ABSTRACT

In a cold climate, the electrical power demand for space conditioning during certain periods of the day becomes a critical issue for utility companies from an environmental and financial point of view. Shifting a portion or all of this demand to off-peak periods can reduce peak demand and stress on the electrical grid. One possibility is to use an electrically heated floor as a storage system in residential houses.

To shift a significant part of the consumption while maintaining occupants' thermal comfort, predictive supervisory control strategies such as Model Predictive Control (MPC) have been developed for forecasting future energy demand. However, MPC requires a building model and an optimization algorithm. Their development is time-consuming, leading to a high implementation cost. This thesis reports the development of a new simplified predictive controller to control an electrically heated floor in order to shift and/or shave the building peak energy demand.

First, a method to model an EHF in TRNSYS was proposed in order to study the potential of using an electrically heated floor (EHF) in terms of load management without predictive control. Some parametric studies on the floor assembly and its impact on the thermal comfort were conducted. Results showed that a complete night-running control strategy cannot maintain an acceptable thermal comfort in all rooms. Therefore, it is required to predict the future demand of the building in order to anticipate the charging/discharging process of the storage system.

Therefore, a simplified self-learning predictive controller was proposed. The function of the proposed simplified predictive controller is to increase the rate of stored energy during off-peak periods and to decrease it during peak periods, while maintaining thermal comfort. To achieve this goal without using a detailed building model, a simplified solar prediction model using available online weather conditions forecast was proposed. The controller approach is based on a learning process; it takes building responses of previous days into consideration. The developed algorithm was applied to a single-storey building with and without basement. Results show a significant decrease in thermal discomfort, average applied powers during peak and mid-peak periods. The approach has also proven to be financially attractive to both supplier and owner.

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Symbols

$E_{applied}^{i}$	Energy applied by the EHF the previous day during the period i [kWh]
E_{mod}^{i}	Modified energy consumption of the previous day for the period i [kWh]
$E_{ini}^{i}(T,S)$	Initial energy consumption for the period i the weather category (T,S) [kWh]
FST	Floor Surface Temperature [°C]
$NMBE$	Normalized Mean Bias Error [%]
PMV	Predicted Mean Vote [-]
PPD	Predicted Percentage of Dissatisfied [%]
T_{in}	Indoor Temperature [°C]
$Tmax_{learning\ process}$	Maximal temperature used for the learning process [°C]
$Tmax_{low-level}$	Maximal temperature used for the low-level controller [°C]
$Tmin_{learning\ process}$	Minimal temperature used for the learning process [°C]
$Tmin_{low-level}$	Minimal temperature used for the low-level controller [°C]
$Tmax_{[X-Y]}$	Maximal temperature during the period from X:00 to Y:00 [°C]
$Tmin_{[X-Y]}$	Minimal temperature during the period from X:00 to Y:00 [°C]
T_{op}	Operative Temperature [°C]

Dimensionless Parameters

BRL	Building Response Learning coefficient
IC	Initialization Coefficient
(T^{i},S^{i})	Weather categories (respectively temperature and solar categories) for the period i

Abbreviations

BITES	Building Integrated Thermal Energy Storage
BIM	Building Information Modeling
EHF	Electrically Heated Floor
FHS	Floor Heating System
IPCC	Intergovernmental Panel on Climate Change
PCM	Phase Change Material
PID	Proportional Integrative Derivative
PWM	Pulse Width Modulation
TABS	Thermally Activated Building System
TRNSYS	TRaNsient SYstems Simulation program

INTRODUCTION

1.1. BACKGROUND

According to the IPCC (GIEC 2013), greenhouse gas (GHG) emissions are the main cause of climate change. Compared to 2010 emissions, it is necessary to reduce them by 70% by 2050 to preserve the ecosystem. The energy sector, including production and consumption, is responsible for two thirds of GHG emissions (Lanoue and Mousseau 2014). Therefore, a significant attention is given to this sector.

The electricity problem in Québec is significantly different than in other countries. While numerous countries should switch their electricity production from fossil fuels to renewable energy, Québec's energy production is already comprised of 99% of renewable energy production, mainly hydroelectricity (Hydro-Québec 2017). Moreover, current plants provide Québec with enough electricity that exceeds the demand by 30 TWh annually (Lanoue and Mousseau 2014).

Despite its high renewable electricity production, intense high peak periods during winter drive Hydro-Québec to activate plants based on fossil fuels and buy expensive energy from its neighbors. To understand where peak periods come from, let us consider the example of a single residential building that illustrates the energy consumption problem. Its electric consumption is not uniform. Because people work during the daytime and sleeping during nighttime, the majority of their household activities (showering, using household appliances, heating the house) happens during early morning and early evening. For a single house, the electricity consumption during these periods may reach 20 times the average consumption (Freris and Infield 2013).

Yet, in an entire electricity distribution network, there is a diversity in building uses (industrial, commercial and residential). Given the absence of simultaneity, this diversity of building functions partly levels the energy consumption. Nevertheless, there still exist peak-periods in the morning and evening. The intensity of these peak-periods depends mainly on the ambient temperature (increase of energy consumption to heat during the winter and to cool in the summer).

For Québec, these peak-periods involve a high electricity production cost. When Québec's suppliers cannot match the supply and demand itself during peak periods, it has to buy electricity from its neighbors at an expensive price (108 $CAD/kW for Hydro-Québec[1] (Hydro-Québec Distribution 2016)). Therefore, a levelled energy consumption profile may decrease the electricity cost for suppliers, and increase opportunities to sell electricity excess at a good price.

In Québec, 30% of the energy consumption is attributed to heating, cooling and lighting buildings (Lanoue and Mousseau 2014), making it one of the main levers for the province . Finding solutions to shift this consumption from peak to off-peak periods may have a significant impact on the entire Québec electricity consumption.

Several techniques have been suggested for shifting peak load. One approach is to encourage users to shift their consumption themselves. Some countries implement price scales depending on the time period: peak periods (higher cost) or off-peak periods (lower cost). The goal is to financially encourage users to use electricity during off-peak periods. There are several types of price scales: with several periods per day ("Time of use"); with a higher price only when the grid is stressed ("Critical peak pricing"); or with a variable price every hour depending on the real price in the electricity market (Guerassimoff and Maïzi 2013). Several studies used these price scales to decrease peak consumption (Atikol 2013; Henze, Felsmann, and Knabe 2004; Oldewurtel et al. 2010).

Another possibility to shift energy consumption is to store thermal energy during off-peak hours and use it during peak ones. The building's envelope, central heating system, and hot water tank have been used as thermal energy storage (TES) (Bastani and Haghighat 2015; Bastani, Haghighat, and Kozinski 2014; El-Sawi, Haghighat, and Akbari 2014; Nkwetta et al. 2014; Nkwetta and Haghighat 2013). The ability of TES to shift energy to low-cost periods is one of its main benefits (Dincer and Rosen 2002). Indeed, during off-peak periods, the heating system can charge the thermal storage system. Then, during peak hours, the thermal energy storage system can release the stored energy, allowing the heating system to remain off or to operate at reduced levels. Moreover, thermal energy storage may be able to reduce the size of a building's heating system and thus its cost. Without thermal storage, the heating system has to satisfy the average load but also peak load. Thus, the heating system's maximum capacity covers only those few peak hours. Coupled with a thermal energy storage system, it is possible to size the heating system based on

[1] Hydro-Québec has a quasi-monopoly position with 77% of the Québec's electricity capacity (Clark et al. 2005)

the average load, while the additional demand during peak periods can be provided by the thermal energy storage system.

Activating the thermal mass of the building envelope through a floor heating system (FHS) is one method for increasing storage capacity. The floor heating system uses an embodied charging system (based on air, water or electricity) to activate a thermal mass. This system is widely used mainly because of its ability to improve the thermal comfort due to a higher operative temperature (Babiak et al. 2009), a better horizontal and vertical air temperature distribution (Khorasanizadeh et al. 2014; Risberg et al. 2015), and an aesthetically pleasing look (Rhee and Kim 2015). In Québec, an FHS is a particularly interesting solution since the slab is the only place with thermal mass. Indeed, Québec residential buildings are mostly made of wood, and often have a basement. Therefore, using this structural thermal mass to store energy during off-peak periods is an attractive solution for solving peak consumption issues.

To increase the peak shaving, many solutions may be used, such as a mechanical system to send the heat to the first floor, or the addition of a PCM layer. However, these systems may be expensive to implement, and may probably be added only to new constructions. Therefore, this study focuses on modification to the FHS control strategy that may significantly shift heating consumption with a low implementation cost. Since the discharge process of a FHS cannot be controlled, the highest amount of energy required should be stored during the night for optimizing the shift of the peak demand while ensuring occupants' thermal comfort. Consequently, this research focuses on the potential of a predictive controller's implementation in terms of peak shaving and occupants' thermal comfort.

1.2. OBJECTIVES

The objective of this research is to examine the ability of an electrically heated floor (EHF) to shift the electrical consumption from peak to off-peak periods. To decrease the peak consumption for the supplier, the proposed solution should accommodate many Québec residences. Three main challenges are highlighted. The proposed solution should:

- Be applicable to residential houses with and without basement
- Have a low implementation cost
- Maintain, in all conditions, occupants' thermal comfort

In light of these challenges, the proposed solution is to develop a predictive control strategy with a low implementation cost. Indeed, a predictive control (i.e. taking weather predictions into account) will predict future loads and therefore store the required amount of energy during the previous night to prevent activating the heating system during peak periods.

From the author's perspective, creating a physical model of each residential house is not conceivable given the high cost of creating a building model. Therefore, this study will aim to develop a predictive control of an EHF to decrease the electrical consumption during peak periods.

To achieve this goal, two tasks are proposed:

- A procedure to develop a model of an EHF in TRNSYS is first realized. The proposed model will then be used in the other parts of the study. Additionally, a parametric study will be conducted on EHF layers' thickness to understand their impact on the EHF performance and study the problematic consequences of a simple non-predictive night-running strategy.
- A control algorithm taking weather predictions into account and providing a shift of the consumption is developed. The implementation cost of the system and the provided thermal comfort will be principally verified. Moreover, in Québec, conventional residential houses have a wooden structure and a basement. Therefore, the only concrete structure is the slab basement. Consequently, this paper investigates the performance of the predictive control on a single-floor house and for one with basement.

1.3. THESIS OUTLINE

Chapter 1 reviews the literature on control strategies for load management applied to building thermal mass. Chapter 2 reports the development of the EHF model, the parametric study, and the developed control algorithms. Chapter 3 describes the results obtained from the parametric study and the developed control algorithms. Finally, conclusions of this research and recommendations for future studies are exposed.

Chapter 2 – Literature Review

This literature review covers thermal mass control strategies in the building for peak shifting or peak shaving. Particular attention will be given to thermal mass activated by a source, either water, air, or electricity. The terminology Thermally-Activated Building System (TABS) is often used, but generally for hydronic systems only. Therefore, the term TABS may be confusing. Moreover, TABS refers only to mechanically activated thermal mass. However, in this study, a passive thermal mass control will also be reviewed. In this study, these systems will be referred to as Building-Integrated Thermal Energy Storage (BITES), following Chen (2013). The term Active BITES will be used for systems with a mechanically activated thermal mass and Passive BITES for a non-mechanical system.

2.1. Non-Predictive Control for Load Management of BITES

For passive BITES, load management with non-predictive controllers may be achieved by modifying the indoor temperature set-point. In cold climates, temperature set-points may be increased before peak periods or decreased during peak periods, while also possibly limiting the power during the peak period. These strategies have been applied in cold climates by Leduc et al. (2011) in a conventional Québec residential house, and by Bastani et al. (2015) in a building with PCM wallboards. The concept is the same in hot climates: temperature set-points may be decreased if no occupancy, maintained at its lower level during the morning, at its higher level during the afternoon, or a combination of these possibilities. These strategies have been applied by Xu et al. (2004) for almost a complete shift in peak consumption. Finally, the transition between two temperature set-points is sometimes studied. Yin et al. (2010) compared results with step, linear or exponential transition between two temperature set-points. Their results showed a greater decrease in consumption during peak periods with a step transition between two temperature set-points.

However, these strategies are limited for residential houses: contrary to offices or commercial buildings, thermal comfort at night must be maintained. Therefore, a significant decrease in peak consumption cannot be achieved only through modification of indoor temperature set-point.

However, for active BITES, the storage system is directly activated by the heating or cooling system. Therefore, the thermal mass can achieve higher/lower temperatures compared to passive BITES (i.e. higher storage capacity) while maintaining a comfortable indoor temperature. More complex control strategies have been proposed to take advantage of the system. This section provides a review of control strategies, limited to shaving or shifting consumption. Their advantages and limitations are discussed relative to providing a good thermal comfort and the possibility of increasing the system's peak-shaving.

2.1.1. Classical Control

Classical control mainly refers to ON/OFF and PID controllers. PI is often preferred to ON/OFF controllers for regulating indoor temperature with active BITES given their large time lag (Li 2010). However, for load management with active BITES, only ON/OFF controllers have been found in the literature.

Kattan et al. (2012) studied a hydronic FHS composed of concrete and an ON/OFF controller. The controller was not meant to reduce consumption during peak periods, yet results showed a significant decrease in peak consumption (26 %) and total energy consumption (30 %) compared to a conventional convective heating system. Nevertheless, it may be difficult to achieve such savings in in conventional buildings. Katthan et al.'s ON/OFF controller was based on the PMV: the FHS water was circulating since the PMV was below -0.5. This control strategy allows taking into account the high floor surface temperature, and thus reduce energy consumption. However, calculating the PMV online involves a large number of sensors, as wall surface temperatures.

Mazo et al. (2012) studied a hydronic FHS with PCM. They chose an ON/OFF controller based on indoor temperature. Their results show a decrease of 78% in peak consumption from adding PCM to the FHS. Therefore, if a decrease in consumption was observed, it is because adding PCM is not because of a profitable control strategy.

In sum, studies sometimes use classical controls to prove the potential advantages of active BITES for load management given the system's time lag. However, the load shifting source is the storage system itself, and not the chosen control strategy.

2.1.2. Intermittent Control

The objective of intermittent approach is to completely shut off the heating system during peak hours. Several authors used a night-running control strategy (often 8h of charge during the night – 16h of discharge) to test the potential of active BITES with PCM to peak shift/shave (Amir, Lacroix, and Galanis 1999; Farid and Chen 1999; Navarro et al. 2015; Yamaguchi and Sayama 1998). However, these studies were designed to show the potential of active BITES with PCM, not to study a control strategy. Therefore, presented results are insufficient for drawing any conclusion about control.

2.1.2.1. Short Intermittent Control

A short intermittent control is means a cessation in the heating or cooling system for a short period of time (a few minutes to a few hours).

Cho & Zaheer-Uddin (1999) studied a two-parameter switching intermittent control on a hydronic FHS. The control strategy, based on a PI controller, used indoor and slab temperatures as control variables. The goal of the strategy was to create switching intervals (between 10 and 60 min) during which the control was based on air or slab temperature, respectively. For the first 10 minutes, they used indoor temperature for feedback, and in the following 10, slab temperature. They tested several heating schedules. Compared to an intermittent control with ON/OFF controller, the indoor temperature variation did not change, but the slab temperature variation decreased by 50%, which may produce a more stable thermal comfort.

Gwerder et al. (2009) and Lehmann et al. (2011) studied a pulse width modulation (PWM) controller, an intermittent ON/OFF controller that controls the water circulation pump. The PWM allows a complete shift in pump consumption for a certain period while maintaining occupants' thermal comfort. To obtain nightly consumption only, they showed that a PWM of 24 hours is required.

2.1.2.2. Night-Running Control Strategy

Several authors studied the possibility of consuming energy only at night. Lin et al. (2005) experimented with an electrically heated floor system with PCM in an environment with an average ambient temperature of 13.6°C. Their control strategy was based on the heating element temperature during the night (heaters stopped working when the temperature was over 70°C and began again when it was below 55°C) and completely shut off during the day. Results showed a poor thermal comfort control with a high average indoor temperature (31°C) and floor surface temperature (40°C).

Li et al. (2009) studied an electrically heated floor system with concrete and micro-encapsulated paraffin of various thicknesses. They investigated some control strategies to shift the peak demand while the heating system operated between 22:00 to 6:00, unless thermal comfort was jeopardized. Results showed an 80% consumption reduction during the peak period. Nevertheless, the simulation was carried out for an office, meaning thermal comfort was studied only between 8:00 and 18:00. Moreover, the study did not report floor surface temperature.

Cheng et al. (2015) conducted simulations and experiments with an electrically heated floor system with a shape-stabilized PCM. The heating time lasted 10 hours and the intermittent time 14 hours, with ambient temperatures between 0°C and 6°C. Results showed that average room temperatures were low (between 15°C and 16°C). Thus, a complete system shut off is not able to satisfy the occupants' thermal comfort.

2.1.2.3. Comparison

Arteconi et al. (2014) studied control strategies for an air deck concrete floor. Their study is particularly interesting since they simultaneously studied the conventional heating curve, a random 15 minutes hourly pause of the heating system, a pause of a few hours (11:00 to 13:00 and 16:00 to 18:00), and a night-running control strategy (with a pause from 8:00 to 20:00). See their load management in **Figure 2.1**. The pause of a few hours is labelled "*Peak-Shifting control strategy*" in the figure.

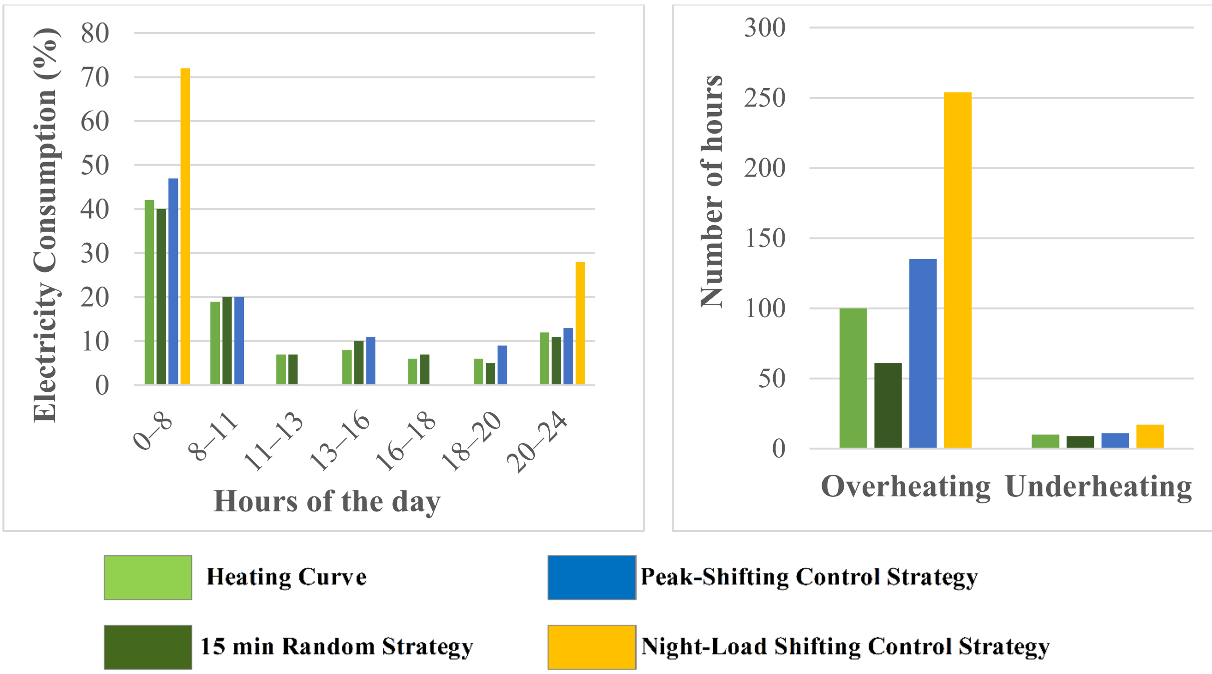


Figure 2.1: Distribution of the electricity consumption of the TABS and the number of hours with over-heating or under-heating as a function of the control strategy (values from (Arteconi et al. 2014))

These results summarized advantages and inconveniencies found in previous studies. Therefore, compared to a conventional control based on heating curve,

- An hourly few minutes pause in the heating system does not shift the consumption but improves thermal comfort.
- A few hours pause in the heating system allows to completely shift the consumption during the stopped hours with only a small increase in thermal discomfort.
- A full day-time pause in the heating system increases thermal discomfort significantly.

In conclusion, a night-running strategy allows a great shift in consumption but may provoke thermal discomfort issues. Therefore, improving the thermal comfort while shifting a high portion of the energy consumption requires predictive control, which predicts future building energy demand and decides what portion should be stored by taking into account the corresponding weather condition.

2.2. PREDICTIVE CONTROL OF BITES

Defining the optimal charge of a storage system may be difficult since storage systems address issues with contradictory effects. On one hand, taking advantage of time-of-use tariffs requires a high amount of energy storage during off-peak periods. On the other hand, the stored amount of energy should not be higher than the building demand, to avoid energy loss or thermal comfort issues in case of storage systems with passive discharge. As a result, a decision process should be able to predict loads in order to increase the storage system's efficiency, a process called "Predictive control".

Building systems control is often divided into three categories (Dounis and Caraiscos 2009; Perera, Pfeiffer, and Skeie 2014; Yu et al. 2015): classical control (mainly on-off and PID), soft or intelligent control (based on historical data) and hard or advanced control (based on a building model). In the case of predictive control, classical controllers as PID cannot be implemented apart from a predictive algorithm. Consequently, some authors proposed supervisory control strategies based on some features (weather parameters with sometimes building and/or storage parameters) to control the storage system, without using building model or historical data. They are defined in this study as "model-free control strategies".

In the case of predictive control, the review will not be limited to studies with a peak-shifting aim. Most of the time, the goal is decreasing energy cost, but since this goal is achieved based on a time-of-use tariff and a shift of the consumption, the result is generally a shift in consumption to off-peak periods. Only studies considering BITES as the storage system will be reviewed here.

2.2.1. ADVANCED CONTROL

In building control, advanced controllers use a building model to determine future operating modes. Three main types of advanced controls, all based on a building model, may be categorized: 1) adaptive control, 2) optimal control, and 3) model predictive control. Adaptive control is based on the adjustment of model parameters (Åström and Wittenmark 2013). Optimal control is based on the optimization of the model to define the optimal control strategy (Kirk 2012). Finally, Model Predictive Control (MPC) is an optimal control based on some predictions. Other advanced controls called "non-optimal advanced control" in this study may be defined. These control systems use building model, but are not adapting parameters, nor apply optimization techniques.

2.2.1.1. *Non-Optimal Advanced Predictive Control*

Reynders et al. (2013) investigated a building integrated with a PV panel, structural thermal mass and a floor heating system. They suggested defining the temperature set-point as a function of the minimal comfort temperature, the building thermal mass, and the building heat loss. A detailed model of the building was used to forecast the demand. The non-predictive control, with a temperature set-point based on the current production and demand, had higher savings than the proposed predictive control. Therefore, this strategy is not advantageous. Gwerder et al. (2008) proposed a predictive control strategy based on heating and cooling curves of a building with TABS, using the Unknown-But-Bounded method. This method takes heat gains' accuracy into account to obtain heating and cooling curves. The concept behind this control is to determine two profiles of heat gains during the day—the lower bound and the upper bound. The lower bound corresponds to the required loads if the external and internal gains have low levels (level of solar radiation low, no occupancy, etc.). The higher bound corresponds to the required loads if the considered external and internal gains have both high levels (high level of solar, maximal occupancy of the building, etc.). Heating and cooling curves are then generated to maintain a satisfactory thermal comfort as long as the real gains are between the defined lower and upper bound. Results indicated that indoor temperature stayed within the defined comfort range most of the time. However, even if it is a simple resistance-capacitance model with limited number of nodes, a room model is necessary for obtaining the room temperature profiles. Moreover, since this model is based on uncertainties, studies in a real building are necessary for testing the controller's robustness.

Therefore, non-optimal advanced predictive control may be a promising way for controlling active BITES. However, at the moment, results did not show a significant improvement in performance. Moreover, the creation of a building model (even a simple one) is still required. Therefore, implementation cost may still be high.

2.2.1.2. *Model Predictive Control (MPC)*

The concept behind MPC is to optimize the system variable(s) as a function of future disturbances for a given horizon in order to satisfy some given constraints. In other words, this supervisory strategy takes into consideration future disturbances to predict the system behavior and calculate an appropriate sequence of operating modes (i.e. the control strategy) to minimize/maximize an objective function (selected based on the operating strategy). This mechanism is illustrated in **Figure 2.2**.

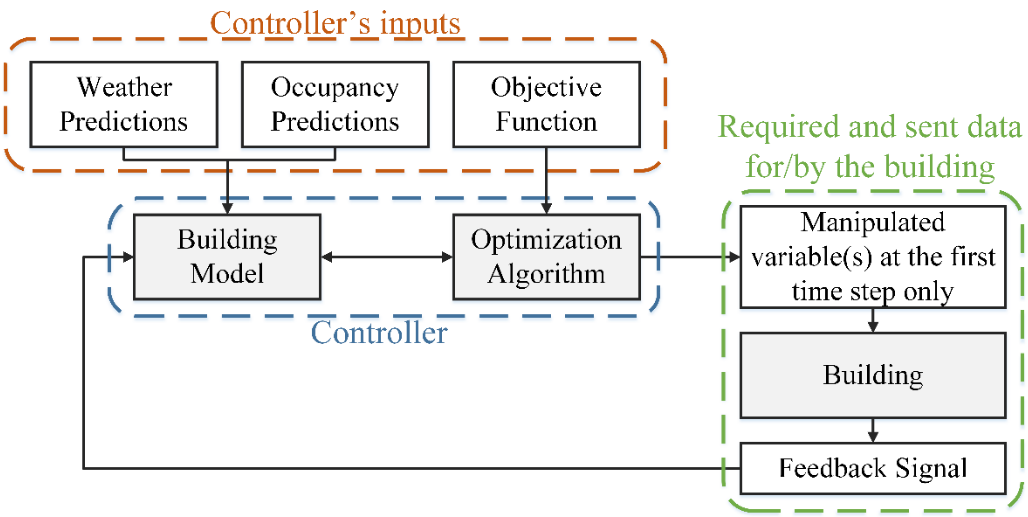


Figure 2.2: Model predictive control for building applications

The main elements of MPC are:

- **Objective function**: The objective function reflects the operating strategy, i.e. the main goal of the control. It may be a simple objective function or multi-objective function (coupling energy consumption and thermal comfort as an example).
- **Prediction horizon**: The prediction horizon is the period of time during which the objective function is optimized (i.e. when the behavior of the system and future disturbances are taken into account to calculate the control strategy).
- **Decision time step**: The decision time step, or "new computation time step" (Kummert, André, and Nicolas 1999), is the duration between each optimization process.
- **Manipulated variables**: Manipulated variables are variables optimized by the controller. It may be variables at a supervisory level (building or storage temperature set-point, operating mode, etc.) or at the component level (air flow rate, power of a system, etc.).
- **Optimization Algorithm:** Algorithm applied in the optimization process.
- **Feedback signal:** The feedback signal provide the required information to the controller for the next time step like the current indoor temperatures. However, it may also be some variables that may be modified by the user as the indoor temperature set-point if it is not a manipulated variable.

MPC is probably the most studied supervisory control strategy for building control currently due to its performance. Results of MPC applied to buildings have been reported by Killian & Kozek (2016) and to HVAC systems by Afram & Janabi-Sharifi (2014). However, results of MPC applied to storage system in buildings has not been widely studied.

Therefore, particular attention will be given to this controller, and the following part will focus on achievements and limitations of MPC applied to BITES.

Thermal Comfort Performance

One of the goals of the MPC application in buildings is to improve thermal comfort (i.e., keep the indoor air temperature within an acceptable range). This goal is mainly a challenge for BITES when the discharge of the energy storage cannot be controlled.

Thermal comfort may be considered in MPC by applying constraints to the indoor air temperature or by using the concept of thermal comfort violations in the objective function. Chen (2002) studied the thermal comfort achieved with a floor heating system with various controllers. He showed that MPC considerably reduced the offset band and the on-off cycling compared to an ON/OFF controller or to a PI controller. Dong & Lam (2014) compared the performance of MPC and a PID in an experimental building with a floor heating system. They concluded that the thermal discomfort was reduced from 4.8% to 1.2% of the time. Finally, Sturzenegger et al. (2016) studied the thermal comfort in a building with TABS. A decrease of more than 50% of the thermal comfort violations was reported compared to a non-predictive controller based on common rules. In short, MPC could improve the occupant's thermal comfort in the case of BITES.

Peak Energy Consumption Performance

On electricity-based systems, considering peak consumption reduction, MPC takes time-of-use tariff (sometimes with peak charge) into consideration in the objective function. Consequently, the controller charges mostly the storage during the low-price periods and discharges it during the high-price periods. Since prices correspond most of the time to the peak/off-peak period, the consideration of time-of-use tariff leads to a shift in consumption from peak to off-peak periods. In the case of passive BITES, peak consumption is reduced by preheating/pre-cooling the building at an acceptable temperature range. Most of the time, the consumption shift is not seen as a goal in itself but as a way to decrease the total energy cost. Therefore, only few studies presented the influence of the MPC on peak consumption reduction.

When passive BITES is the only storage technique, the shift of a part of loads may be achieved by optimizing the temperature set-point. On the one hand, during off-peak periods, temperature set-point is increased for heating and decreased for cooling to store energy at a cheaper cost (preheating/pre-cooling). On the other hand, during peak periods, the temperature set-point is decreased for heating and increased for cooling to reduce the power demand. Braun (2003) optimized indoor temperature set-point with MPC considering the total energy consumption of the building but also the maximum demand. He observed a demand reduction during peak periods between 15% and 35% compared to conventional control strategies. Oldewurtel et al. (2010) compared results using MPC with a constant tariff and a time-of-use tariff. Considering several building archetypes, they reported an average reduction of 7.9% in highest peak demand when using a time-of-use tariff compared to a constant tariff. Oldewurtel et al. (2011) performed a similar comparison (constant tariff / time-of-use tariff) as a function of the building archetype. A decrease in consumption during peak periods from 4% to 19% depending on the building archetype was reported with the largest reductions for heavy buildings. If these studies showed a significant decrease in peak consumption for passive BITES with MPC, effects of MPC with active BITES on peak demand have not been studied.

Total Energy Consumption Performance

Considering the total energy consumption, **Table 2.1** summarizes energy savings as a function of storage system type.

In summary, most studies are simulations based (sometimes with experimental chambers) thus with limited applications to real buildings. Moreover, results are highly different for energy savings (from -29 % to + 33 %) and cost savings (from 4 % to + 47 %). These discrepancies make it difficult to draw any general conclusion about the performance of MPC for storage systems. Most of the studies are only specific cases. However, to explain this discrepancy, some researchers conducted parametric studies or compared some results to detect features that have a strong influence on the controller performance. Previous work mainly focuses on:

- The thermal mass of the building (Cigler, Gyalistras et al., 2013; G. Henze & Krarti, 2005; X. Li & Malkawi, 2016)
- The climate and the season (Hazyuk, Ghiaus, and Penhouet 2014; Henze and Krarti 2005; Kummert, André, and Argiriou 2006; Li and Malkawi 2016).

- Time-of-use tariff considered when cost savings instead of energy savings are considered (Braun 2003; Collazos, Maréchal, and Gähler 2009; Henze and Krarti 2005; Li and Malkawi 2016; Morgan and Moncef 2010; Oldewurtel et al. 2011)
- The desired level of thermal comfort (Li and Malkawi 2016) and the proportion of occupied and non-occupied hours (Braun 2003)
- The level of internal gains (G. P. Henze et al., 2010; Zakula, Armstrong, & Norford, 2015)
- The considered hypotheses for the model, the occupancy and the weather forecast uncertainties (Schirrer et al. 2016)
- The prediction horizon (Kummert et al. 1999)

Table 2.1: Energy savings with MPC reported in studies with MPC and storage system

	Reference	Type of storage	Type of experiment	Renew. Energy	Weather Pred. Mismatch	Compared control	Savings	Criteria
Active BITES	(Ren and Wright 1997)	Hollow core ventilated slab	Simulation	No	Considered	Thermostat	4 % -29 %	Cost Energy
	(Ihm and Krarti 2005)	FHS	Simulation	No	Not considered	Proportional controller on air temperature	22-30 %	Energy
	(Prívara et al. 2011) - (Široký et al. 2011)	Ceiling heating system	Real building	No	Considered	WCC Preheating during the night	17-24 % 15-28 %	Energy Energy
	(Dong and Lam 2014)	FHS	Ex. Building	No	Considered	Night set-back	30.1 %	Energy
	(Salque, Marchio, and Riederer 2014)	FHS	Simulation	GSHP	Considered	Thermostat (air temperature) Thermostat (floor surface temperature)	6 % 17 %	Energy
	(Sturzenegger et al. 2016)	TABS	Simulation	No	Not considered	Rules based controller	17 %	Energy
	(Feng et al. 2015)	Cooling radiant slab	Simulation	No	considered	Rules based controller	14.4 %	Energy
	(Killian, Mayer, and Kozek 2016)	TABS	Simulation	No	Not considered	Rule-Based PID	0.4 %	Energy
	(Cho et al. 2012)	FHS	Ex. Chamber	No	Not considered	Constant set-point WCC	12.5 % 6.7 %	Energy
	(Masy et al. 2015)	FHS	Simulation	No	Not considered	Intermittent heating	33 %	Energy
Active BITES and TES	(Mayer, Killian, and Kozek 2016)	TABS and chiller storage	Simulation	GSHP	Not considered	PID control	47 %	Cost
Passive BITES and active TES	(Henze, et al. 2004)	Passive Active Passive and Active	Simulation	No	Not considered	Chiller Priority Control	20 % 20 % 46 %	Cost
	(Hajiah and Krarti 2012a, 2012b)	Ice storage and thermal mass	Simulation	No	Not considered	Constant Temperature set-point Chiller priority control	16-28 % 7-20 %	Cost
	(Liu and Henze 2006b)	TES Tank and thermal mass	Simulation	No	Not considered	Night set-back Storage-priority -night set-back Learning control	33 % 26 % 26 %	Cost

To understand results better, some parametric studies have investigated the influence of building thermal mass and orientation, the climate and the season, the time-of-use tariff and the accuracy of weather predictions as (Henze and Krarti 2005) for passive BITES and (Gyalistras and Gwerder 2009) for active BITES activated by water. Furthermore, **Table 2.1** evidences the considerable diversity of comparative basis concerning the controller. This multiplicity makes comparisons between results of studies difficult.

In summary, MPC proved having a high potential for improving the performance of buildings with BITES in terms of thermal comfort, peak demand, or total energy cost. Therefore, MPC seems to be an interesting controller for this study. Nevertheless, these conclusions have to be qualified and cannot be applied to any type of building with BITES. At the moment, MPC for storage system in buildings is not a common practice. To be widely implemented, MPC still has to overcome some challenges.

Challenges and Issues of MPC

MPC is based on a building model that predicts loads and production for renewable energy utilization, which is a time-consuming process. Cigler et al. (2013) reported that 50% of the time spent setting up a model predictive control is for MPC model development, and this proportion rises to 80% in an industrial implementation (Cigler et al. 2013). By adding a storage system, the required time may increase further. The large amount of time required for its development is one reason for MPC's current high cost.

Moreover, if different types of building models are applied, they all suffer some shortcomings:

- A black-box model, based only on historical data, needs a long training period and the model extensibility is limited to the quality of training data.
- Grey-box models, using partial physical model and historical data, are based on parameter identification and a simplified building model. However, the latter needs expert knowledge and the former is time-consuming. Moreover, the parameter estimation results highly depends on the data set (as for black-box model), whether it be a theoretical data set or a measured one (Sourbron, Verhelst, and Helsen 2012).
- A white-box model, based only on a physical model, is time-consuming to validate, and often has a low computation speed. Moreover, white-box model has to be linked to an optimization process. Some tools have been proposed for developing the building model and the

optimization algorithm on the same software as Modelica (Wetter 2009). However, at the moment, the building simulation community uses mainly software having no optimization process like TRNSYS or EnergyPlus. In consequence, building model software tools must be linked to some optimization tools (Matlab, GenOpt, etc.), which may be difficult to achieve or reduce the modeling possibilities. Nowadays, in addition to the building model layer and the optimization layer, an organization layer may be implemented to allow softwares to be linked. This organization layer may be implemented using software like BCVTB (Wetter 2012), which has already been used for real-time building energy simulation for building integrated with energy storage system (Kwak and Huh 2016; Kwak, Huh, and Jang 2015).

Moreover, after developing the building model, the computation time due to the optimization process is one of the main challenges of MPC even without a storage system. Adding an energy storage system can complicate the optimization process. For instance, the optimization process has to determine the time and amount of demand, time of charging/discharging and from which source (grid or renewable energy). Since the number of subsystems increases, the number of inputs, state variables and outputs that have to be taken into account in the global optimization process increases too. Consequently, computation time and the complexity of the optimization process (non-convexity, non-linearity, etc.) may increase.

Finally, there is the problem of uncertainties. MPC is based on prediction of future disturbances (weather forecast and occupancy). However, many studies consider a perfect forecast. Of course any prediction has, in reality, some uncertainties that may impact system performance. For buildings, the accuracy of some predictions is low (particularly solar radiation and occupancy). Therefore, the controller may receive inaccurate information, leading to incorrect actions that may cause some thermal discomforts.

Some researchers have studied the effect of uncertainties on the performance of MPC in buildings integrated with an energy storage system. For weather predictions, uncertainties may originate from two different sources—the prediction process and the building location. The exact information about terrain characteristic difference between the weather station and the actual building location could be the source of the prediction uncertainties. This error may be greatly decreased by a Kalman filter (Gyalistras and Gwerder 2009). Considering the controller prediction process, ambient temperature error does not have a major impact on the thermal comfort and energy performance (Ren and Wright 1997), but uncertainties in predicting solar radiation may impact thermal comfort conditions significantly (Candanedo, Allard, & Athienitis, 2011; Gyalistras & Gwerder, 2009).

The second source of uncertainties is occupancy. In earlier studies, occupancy was modeled in a simple manner, with occupancy schedules. However, occupancy has great variations and is predicted with difficulty (Yu, Haghighat and Fung 2016). This may have a significant impact on the building energy load and consequently on the controller performance of the storage system, whether it is energy performance (Ma, Kelman, Daly, & Borrelli, 2012) or both energy and comfort performances (Schirrer et al. 2016) in the case of BITES.

To conclude, MPC has been widely studied and may provide benefits for thermal comfort, energy consumption, peak consumption and energy cost. However, to achieve a wide-scale implementation, MPC has to overcome the following shortcomings:

- Significant amount of time to develop a model for a building and its storage
- Difficulty in linking the optimization process with conventional energy simulation tools
- Complex optimization process that may lead to a long computation time and difficulties in its formulation
- Uncertainties in weather and occupancy predictions that may lead to high thermal comfort issues in the case of BITES

To overcome these issues, new formulations have been proposed in the literature. First, the consideration of uncertainties in MPC is reviewed. Then, simplified MPC formulations that were proposed are evaluated.

Consideration of Uncertainties in MPC

As shown earlier, uncertainties in weather and occupancy predictions may cause thermal comfort issues for BITES. Several MPC formulations have been developed, taking uncertainties (most of the time weather forecast uncertainties, but sometimes also model or occupancy mismatch) differently into account: stochastic and randomized MPC, and adaptive MPC.

A stochastic system is a dynamic system that has some uncertainties: disturbances acting on the system, sensor errors, and unknown dynamics of the system (Söderström 2012). In MPC's framework, stochastic MPC takes prediction uncertainties into account using probability distributions. Consequently, the optimization process considers these uncertainties when choosing the optimal value for control variables.

Considering disturbances brings more complexity to the optimization process, accentuating the computational issues of MPC. Two different approaches have been used:

- Stochastic MPC, which considers disturbances as a sequence of bounded, independent and identically distributed random variables or follow a specific distribution (Prandini, Garatti, and Lygeros 2012). For building and storage systems, weather forecast distribution is often presented by a Gaussian function (Zhang et al. 2013).
- Randomized MPC, particularly the scenario approach, which leads to pick a certain amount of uncertainty levels and treats them as if they were the only possible uncertainties.

Only a few studies have applied stochastic or randomized MPC for building control with storage system. Oldewurtel et al. (2012) compared a stochastic MPC with Gaussian assumptions to a standard Rule-Based Control and a deterministic MPC. Their results indicated that stochastic MPC decreased the number of thermal comfort violations and their deviations. However, only disturbances in weather predictions have been taken into account, not uncertainties on occupancy. Ioli et al. (2016) considered a randomized scenario approach optimization algorithm for considering uncertainties when controlling a building with a chiller plant and active storage system and passive BITES. Their results using only the passive BITES showed a 9% decrease in cooling costs with the randomized MPC compared to a deterministic MPC. Comfort violations were not compared.

In summary, stochastic MPC led to improved thermal comfort for passive BITES. However, adding uncertainties to the optimization algorithm increases its complexity, and thus the computation time.

The second possibility for incorporating uncertainties is using an adaptive process. Schmelas et al. (2015) proposed an adaptive MPC using a resistance-capacitance model of the TABS and a regression algorithm. Regression coefficients were calculated based on historical data using ordinary least squares method. Energy demand for the next day was predicted based on these coefficients and the weather forecast. Coefficients were updated with new measured data to react to a change in internal gains. Based on results obtained in laboratory test, thermal comfort was improved with the adaptive MPC method compared to the outside temperature compensated control. Moreover, they observed a 70% decrease in pump running time compared to the weather compensated controller (WCC). The controller was then tested in a real building for one month (Schmelas et al. 2016). Their results showed a consequential improvement in thermal comfort as well as large energy savings (a 41% energy consumption decrease). These savings are partially due to a decrease of building over-heating. This study on adaptive MPC is the only MPC formulation considering uncertainties having been used in real building with storage system to the authors' knowledge.

In summary, some MPC formulations considering weather or occupancy uncertainties lead to a decrease of thermal comfort issues. Moreover, it demonstrates a good performance even in occupied building. However, uncertainties account increases the complexity of the optimization algorithm and thus the computation time as well. The increase in computation time also increases the cost of the controller. Consequently, using stochastic or adaptive MPC to deal with uncertainties is inconvenient considering this research's challenges regarding the implementation cost issue. Therefore, simplified MPC formulations for BITES are reviewed in order to find a solution to the computation time issue.

2.2.1.3. Simplified MPC Formulations

To decrease the complexity of MPC, new formulations have been proposed. A focus is given in this study to distributed MPC and pre-computation.

Distributed MPC

To gain insight into distributed MPC, it is first necessary to understand the difference between centralized and decentralized MPC. On one hand, decentralized MPC considers one MPC for each zone or device. A decentralized MPC is easy to implement and has a fast computational time but disregards thermal influence of zones or the impact of systems on each other (as storage and building if they are modeled separately). On the other hand, centralized MPC considers inputs and outputs of each zone or system in the same controller. This MPC formulation is the most commonly used approach for buildings with storage system. However, when the number of zones or systems is high, the computational time may become high too. To address this problem, one solution is to build a distributed MPC, which is a hybrid of decentralized and centralized approaches.

The concept behind distributed MPC is to have one MPC for each zone or device with the possibility for each to exchange information with other MPC. Other studies also define a hierarchical MPC, a distributed MPC with two controllers that communicate in a specific direction. These 4 MPC configurations are illustrated in **Figure 2.3**.

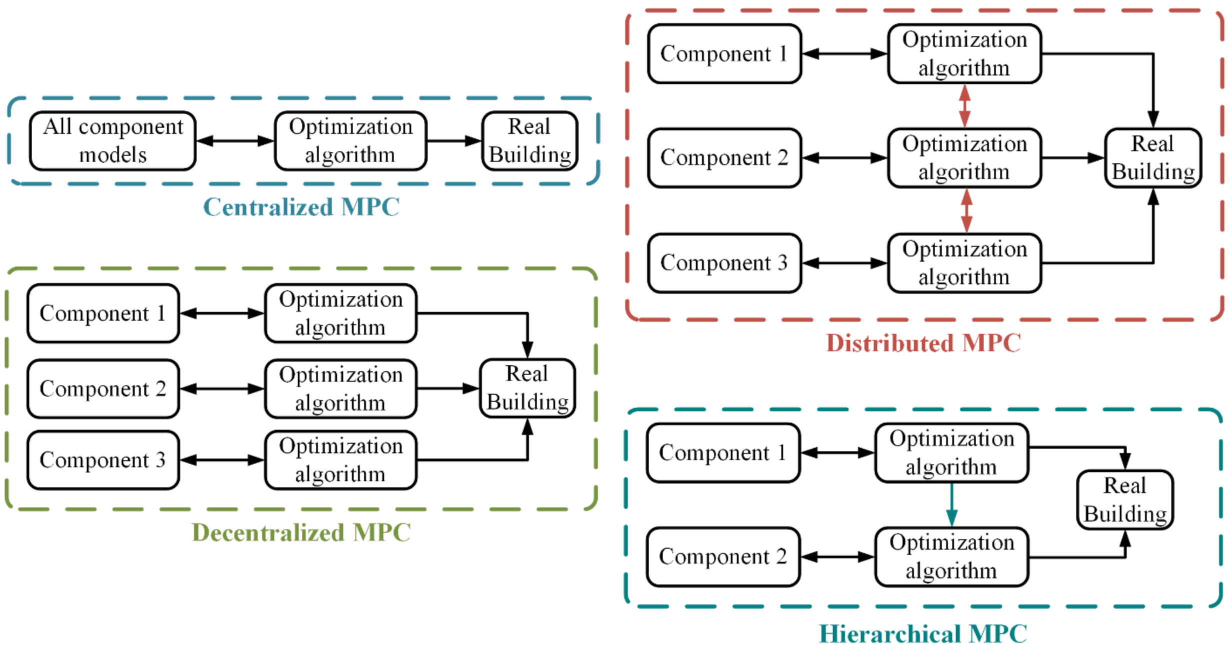


Figure 2.3: Differences between centralized, decentralized and hierarchical MPC

A distributed MPC considers several MPC that are able to communicate. This configuration is widely used at the community level to manage the consumption of each building, storage use, and sometimes renewable energy consumption (Chandan et al., 2012; Cole et al., 2014; Larsen, Van Foreest, & Scherpen, 2014; Ma et al., 2012; Patel, Rawlings, Wenzel, & Turney, 2016). Compared to single building studies, the question of distribution system is added.

For a single building with BITES, most distributed MPC found in the literature may actually be considered as hierarchical MPC since they always have only two levels and communicate in a specific direction. Only one distributed but non-hierarchical MPC has been found in the literature: Killian et al. (2016) proposed a distributed MPC for a building by considering one MPC for each zone (based on the orientation, i.e. 4 zones). They developed 3 models for each zone - a total of 12 models. The 13th model is used to simulate the TABS. First, MPC of each zone optimizes the supply temperature of the fan coil for each zone, and the MPC for the TABS optimizes the supply the TABS' temperature. A cooperative iteration-loop is proposed, adjusting results of each MPC as a function of the others.

Other studies are based on hierarchical MPC. If the separation between levels may be different depending on the study, a general trend may be extracted:

- The high-level MPC is a long-term controller. It gives a first tendency in the origin of the required energy: Is there enough renewable energy for the building? When should energy from the grid be stored? When should it be used? etc. Therefore, the high-level controller mainly optimizes storage variables (indoor temperature set-point for passive BITES, storage temperature set-point or operating modes of the storage for active BITES)
- The low-level MPC often considers a shorter prediction horizon. Most of the time, the low-level controller is used for tracking the building temperature set-point particularly when subjected to disturbances or for tracking the energy consumption optimization.

While having a long-term high-level MPC and a short-term low-level MPC is common, it is not always the case and the selected set of manipulated variables may be different. In what concerns the integration of BITES in buildings, the hierarchical MPC may be divided into two categories depending on their high-level controller's goal: optimization of the storage system or exchange energy between systems.

Some studies first optimized storage system variables. Ren & Wright (1997) performed a study in a building with a ventilated slab. They proposed to implement a high-level controller that optimized all variables linked to storage system: indoor temperature set-point for passive BITES, start up and shutdown times and the airflow rate of the ventilated slab for active BITES. Based on values obtained by the high-level controller, the low-level controller optimizes operating heating and cooling plants modes to minimize the energy cost. Consequently, the low-level controller stopped or started the heating/cooling and the heat recovery system following the defined temperature set-points. Similarly, Ioli et al. (2016) suggested a two-level MPC in a building with integrated passive or active storage. On one hand, their high-level MPC optimized tank and building temperature set-points, and on the other hand, the low-level controller tracked the building temperature set-point.

Some studies first optimized allocation between systems (i.e. when each system will work). Mayer et al. (2016) studied a hierarchical MPC in a building with a chiller storage and TABS. The high level controller optimized trajectories of cooling demand of TABS (provided by a geothermal system) and fan coil system (provided by the storage and the chiller). According to these demand trajectories, the low-level controller optimized mass flow rates and operational time of the systems.

In sum, a high number of studies proposed to use hierarchical MPC. Indeed, this type of formulation allows systems to be separated with different time lag and increase the robustness of the controller in considering different prediction horizons. Therefore, a significant decrease in computation time may be achieved. Consequently, a hierarchical control is particularly interesting for reducing the computation time while ensuring occupants' thermal comfort.

Going without Real-Time Dynamic Optimization

To decrease the computational time, another solution suggested completely removing the online optimization process. The concept behind this formulation is to implement the MPC only offline and thus create a simpler supervisory control, often based on other control techniques.

Several types of supervisory controls have been developed and used on buildings with storage system, as pre-computed tables (Coffey 2012; Kim 2013), affine function (Klaučo et al. 2014) or decision tree (May-Ostendorp and Henze 2013).

However, this technique has not been applied to active BITES but only to passive BITES coupled with a learning process. Liu & Henze (2006a, 2006b) proposed a hybrid simulated reinforcement-learning controller. The concept behind this control is to first train a MPC with a simple building model. This offline learning saves time compared to the online learning process. Then, the controller is implemented in the real building, controlling the building but also learning from its response. They realized an experimental study in a laboratory building with an internal melt ice-on-tube thermal energy storage tank and passive BITES. They prevented a larger number of modes switching by stopping the TES tank charge during peak periods and discharge during off-peak periods. It showed similar results to a storage priority controller using a load predictor. The use of offline MPC with learning process allows a reduction of both computation time and required building model accuracy.

In sum, using no real-time dynamic optimization decreases computational time significantly, one of MPC's main issues. However, a large data set has to be created for each building, involving a large number of simulations. Consequently, this technique may be time-consuming to implement and thus too expensive to realize for industrial applications.

Therefore, if MPC proved to provide a good performance for BITES, there is no formulation that completely solves MPC challenges, particularly its implementation cost issue. A building model requirement always leads to an implementation cost that cannot be considered for a large-scale application. Therefore, other predictive control strategies, not based on a building model, have been proposed in the literature.

2.2.2. Other Predictive Control

2.2.2.1. Intelligent Controller

Intelligent controller is a class of controllers using information from previous data records and applies advanced techniques such as artificial intelligence to provide comfortable indoor conditions. Some studies use artificial intelligence to control a building with thermal energy storage system (Henze and Schoenmann 2003), but the number of studies using intelligent control based on prediction applied to a storage system is limited. Lebreux et al. (2006) and Lebreux et al. (2009) suggested combining a fuzzy logic controller and a feed-forward controller with weather predictions to control an electric wall heating system integrated with a solar energy production system. The fuzzy logic controller determined the amount of energy needed to be stored. To create this controller, the authors fixed 27 rules based on their personal expertise as a function of: 1) the level of estimated energy losses from the renewable energy system, 2) the forecasted solar radiation, and 3) the amount of energy stored during the previous day. When the amount of energy that had to be stored is determined, the feed-forward controller determined the heating consumption profile during the determined off-peak hours. The feed-forward controller was based on an offline learning process: all heating consumption profiles were tested under various weather forecasts. The resulting thermal comfort in the room was studied for each profile, and the profile with the best thermal comfort was selected for each weather forecast. An electric fan controlled the temperature to ensure a good thermal comfort. Their results indicated that 94 % of the energy was consumed during off-peak periods. This control was able to provide good results, but it needed an experienced user to set the rules (the main limitation of this approach).

2.2.2.2. *Model-free Control Strategies*

As explained previously, the concept behind model-free control strategies is the use of weather predictions without building model or historical data. These control strategies manipulate directly heating/cooling system variables or temperature set-points.

Cho & Zaheer-Uddin (2003) conducted a study with a building including a hydronic floor heating system. The authors proposed to modify the intermittent scheduled control, a fixed heating schedule based on minimal ambient temperature for the next day. Several ambient temperature ranges are defined with a specific heating schedule for each. Therefore, the controller was based on weather predictions. However, considering that this control is often conservative (too much heat is provided), they suggested fine-tuning the heating schedule to correlate the exact length of each heating cycle to the specific minimal ambient temperature for the next day. Their results showed a decrease in indoor air temperature fluctuations and a 10% to 35% reduction in energy consumption depending on weather conditions. Energy savings were higher for mild and hot days than cold days. However, it is important to note that a part of this decrease was due to the decrease of the average indoor air temperature for all the cases analyzed. Moreover, experimental studies were realized in non-occupied facilities. Consequently, effects of occupancy were not considered.

Most of the time, temperature set-points are controlled. Chen et al. (2014a; 2014b) suggested determining the indoor temperature set-point profile of a building including thermally activated building system (TABS) to take advantage of external gains. Weather forecasts (predicted ambient temperature and solar radiation) were used to determine high-peak and low-peak sol-air temperatures for the next day. The temperature set-point profile was then calculated based on sol-air temperature, time lag of the building and acceptable indoor temperature range. They carried out a parametric study on the time lag between solar radiation (i.e. charge of the storage system) and peak indoor temperature as a function of the concrete slab thickness, the location of the energy source in the concrete, and the global thermal mass level of the building.

Also using temperature set-points control, Alimohammadisagvand et al. (2016) studied the control of a building with a floor heating system and a hot-water tank. They tested a control algorithm based on future values of hourly electricity prices. The concept behind this control was to adapt the building temperature set-point and the water tank temperature set-point as a function of the future trend of the electricity price. Results showed a 5.0 % to 6.9 % decrease in electricity consumption. Finally Barzin et al. (2016) proposed a predictive control for a hut with PCM-impregnated gypsum wallboard. Considering the wall temperature as the storage temperature set-point, they proposed to control it as a function of two parameters – the cloudiness of the sky and the dynamic electricity price. They defined an optimal price which was a limit between the on-peak and off-peak electricity price. The controller determined the wall temperature set-point as a function of the cloudiness forecast and the situation of the current electrical price compared to the optimal price. Consider two examples: if a sunny day was predicted, the wall temperature set-point was fixed at its lower level; on the contrary, if a cloudy day was predicted, the wall temperature set-point was fixed depending on the electricity price (higher level if the online electricity price was low and lower level if the online electricity price was high). They realized an experimental study on two huts. Compared to results without predictions and without PCM, the thermal comfort was greatly improved and they reported price and energy savings by 41% and 30%, respectively. However, the proposed control lead sometimes to serious thermal discomfort issues. As an example, they studied a sunny day that was predicted as cloudy, when indoor temperature was high and energy consumption increased by 73% compared to the other hut.

Consequently, earlier studies showed that this type of controller provides promising results, but may cause some thermal discomfort in the case of passive discharge storage mainly due to weather uncertainties. Moreover, this type of controller has not been tested yet in real buildings and a model-free control strategy able to shift a significant part of the consumption without time-of-use tariff was not proposed. Nevertheless, their low cost is adapted to a large-scale application and their intuitiveness may help occupants' acceptance. Consequently, predictive model-free controllers seem an interesting approach to such application.

2.3. Summary and Limitations of Previous Studies

The goal of this review was to realize the state-of-art of the control of BITES for load management, and particularly active BITES. If many studies focus on BITES and their control, the number of studies that have reported a good performance in terms of peak-shifting and thermal comfort at the same time is quite low. From one perspective, intermittent non-predictive control strategies allow a great shift in consumption, but may involve occupants' thermal comfort issues. Moreover, studies applying a night-running control strategy are mainly using an active BITES with PCM but not with concrete only. From another perspective, MPC showed a high performance in thermal comfort or energy consumption. However, its performance depends on many parameters that should be considered before using it. Moreover, results of some studies should be refined since most of them are simulations based, without consideration of all/some uncertainties (weather, occupancy and model uncertainties). Finally, and the most important for this study, MPC still has to overcome some challenges. Indeed, even if some MPC formulations have been developed in order to decrease computation time or increase the robustness of the controller to uncertainties, MPC still needs a building model. If the increase of the use of Building Information Modeling (BIM) may be a solution for large buildings, these MPC formulations may not be the solution for this research. Considering a widespread residential application, the creation of a building model and the implementation of an optimization process, as simple as they may be, will remain expensive. Therefore, for this application, the use of MPC is not a good solution.

Otherwise, predictive model-free controllers, simple and cheap to implement, may perform better than conventional controllers without adding too much complexity. Moreover, their intuitiveness may help the occupant's acceptance to the controller. However, thermal comfort is not always satisfied in reviewed studies. Moreover, their application has not been tested on real buildings and a model-free control strategy able to shift a significant part of the consumption without time-of-use tariff was not proposed. Consequently, developing a predictive model-free controller seems a particularly interesting approach to achieve the objectives of this research.

Therefore, a predictive model-free controller, allowing a shift of the heating demand and ensuring a good thermal comfort, is proposed in this work. The author has followed previously proposed model-free controllers, but also used formulations of the other types of controllers (e.g. hierarchical controller, pre-computation, or learning process) to create a simplified self-learning predictive controller applied to an EHF.

To develop this controller, an alternative modeling of an EHF in TRNSYS is first proposed and a study on the potential of an EHF for load management is conducted. Then, a solar prediction model is developed and used in the developed simplified self-learning predictive controller. Finally, the proposed self-learning controller is compared to some non-predictive controllers to study its performance regarding thermal comfort, average applied power during peak and mid-peak periods, and financial costs.

Chapter 3 – Building Models and Methodology

3.1. Presentation of the Hydro-Québec Building

3.1.1. Experimental Building

For this study, a traditional residential Québec house built in the 1960's was used. This building is presented in **Figure 3.1**.

Figure 3.1: The experimental residential house used

This building is located in Montréal (Québec, Canada), where ambient temperature varies between −27 °C and 1°C in January. The building has a basement with 6 rooms and a ground floor with 6 rooms. A TRNSYS model was created by Aongya (2010) for the Laboratoire des téchnologies de l'énergie d'Hydro-Québec. Adding the hallways and the attic, 16 zones have been created (7 in the first floor, 8 in the basement). Occupancy was modeled in this building model considering a different schedule for each zone and for week days and week-end.

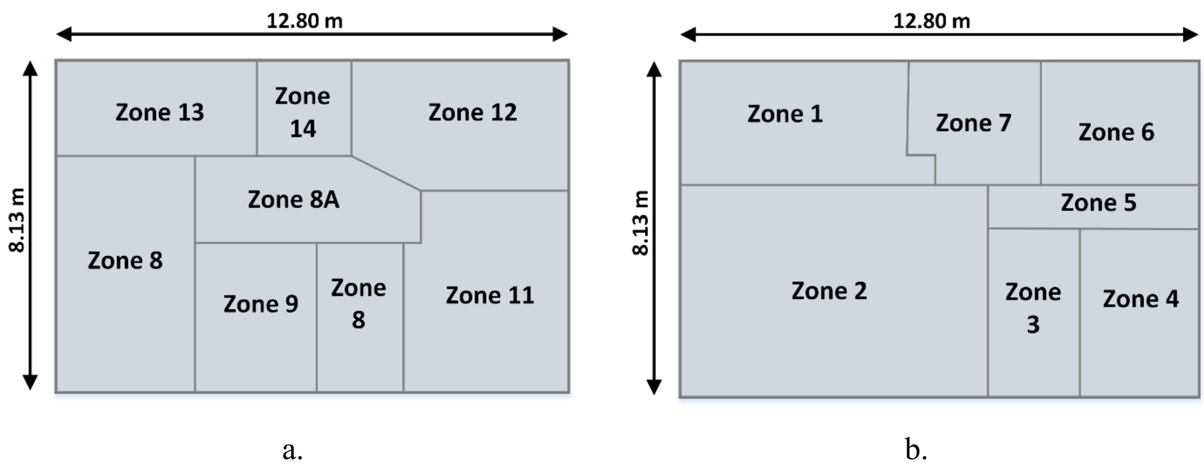


Figure 3.2. Zones of the experimental building (Aongya 2010).

a. Basement. **b.** Ground floor

TRNSYS is the abbreviation for TRaNsient SYStems simulation program. This software works with modules called "*types*", mathematical models in which users can choose to link inputs and outputs of different *types* together in order to study the performance of a system. The format of the program makes this software highly flexible.

To model a building in TRNSYS, several *types* may be used. Particularly, *Type 56* is used in order to study the thermal behavior of a multi-zone building (Madison et al. 2009). This *type* enables to model the complex behavior of a building by taking into consideration many geometric parameters (thicknesses, surfaces, positions of zones, etc.), but also weather data and occupancy schedule. *Type 56* was used to simulate the residential building used in this research. The simulation was validated with measured field data (Aongya 2010) and used in previous studies (Bastani et al. 2015).

3.1.2. Modifications

Originally, this building was heated using electric baseboards. The building was modified to meet the requirements of this project: the existing heating systems (electric baseboard) were replaced by EHFs at the basement level with the method explained in paragraph 3.2.1. The convective heat transfer coefficient of the floor heating system was set at 3.05 W/m^2.K (Cholewa et al. 2013). To calculate the radiative heat transfer, TRNSYS considers the emissivity of surfaces (0.9 in this study) and properties of materials presented in **Table 3.1**.

Table 3.1: Thermophysical properties of floor layers

Thermophysical properties	Conductivity (W/m·K)	Specific Heat (kJ/kg·K)	Density (kg/m^3)
Concrete	2.25	0.99	2200
Insulation (XPS)	0.04	1.5	35
Floor Covering (plywood)	0.164	1.63	670

Then, the radiative heat transfer is distributed proportionally at the surfaces. The floor assembly of the EHF consists of four layers presented in **Figure 3.3** for the reference case. The reference case is the assembly currently installed in Québec houses.

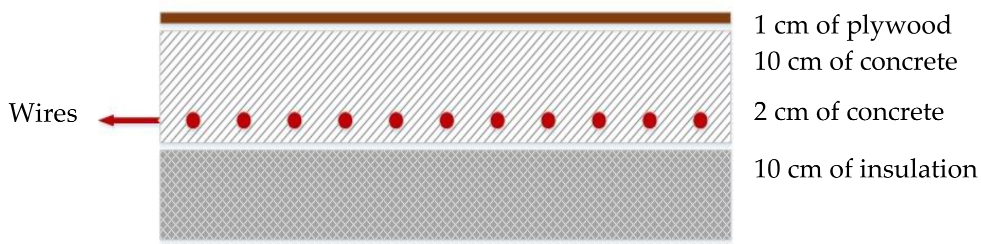


Figure 3.3. Electrically heated floor assembly — reference case.

Moreover, a second version of this building was created. The basement was erased in order to create a one-storey building. If preliminary studies are usually conducted on only one building model, final comparisons of the controllers' performance are presented for both buildings to cover most types of residential dwellings in Québec.

Finally, the coupling between the building and the ground was modified. This modification is explained more in detail in the paragraph 3.2.1.4.

3.2. Task A: Study of an EHF in TRNSYS with a Load-Shifting Aim

3.2.1. Task A.1: Modeling an EHF in TRNSYS

3.2.1.1. Existing Methodologies for EHF in TRNSYS

To model the EHF in TRNSYS, two methods can be used.

The first method is the use of the *wall gain,* "an energy flux to the inside wall surface" (Madison et al. 2009). Considering that "wall" in TRNSYS means an actual wall, floor or roof, the *wall gain* simply defines a given heat flux on a surface. However, the *wall gain* can only be implemented on top of the surface and not within it, and may consequently change the storage system behavior.

It is also possible to use the *active layer* designed for hydronic floor heating systems. By choosing a high water flow rate, a constant water temperature can be assumed; it can then behave as an EHF. Nevertheless, using the active layer requires determining the relationship between the parameters of the active layer (flow, pipe diameter, pipe conductivity, water temperature, etc.) and the EHF power. Moreover, to use this type of layer, some hypotheses must be verified (Madison et al. 2009), which may limit the parametric study.

For this study, the *wall gain* method was selected, with some modifications to go beyond the presented limit.

3.2.1.2. Integration of the EHF

Some modifications must be made to the floor assembly to model the building integrated with an EHF and use the *wall gain*. In an EHF, heating elements are uniformly placed within the concrete. This way, the power is evenly distributed and the concept of constant power gain can be applied to EHF. A *wall gain* was then used to model the heat flux.

However, the *wall gain* can be used only on the top or bottom of a floor assembly but not within the latter. Therefore, to apply this surface gain for this project, a "fictitious" zone was created below the room zone, as presented in **Figure 3.4**. By setting an infinitesimally small air volume and assuming a high heat transfer coefficient for the "fictitious" zone, a perfect contact between two layers can be assumed. In addition, the perimeter heat losses were neglected since the height of the air node of the "fictitious" zone is infinitesimal.

This fictitious zone has one floor (connected to the ground) and one ceiling (connected to the room zone) (see **Figure 3.4**). Together, these two zones represent all layers of the floor assembly. The *wall gain*, used as a surface gain and modeling the EHF elements, was added on the upper-surface of the lower-wall (between the Floor_1 and Floor_2) to model the wires (see **Figure 3.5**). The total thickness of each material (insulation, concrete and plywood) is the same in the two configurations.

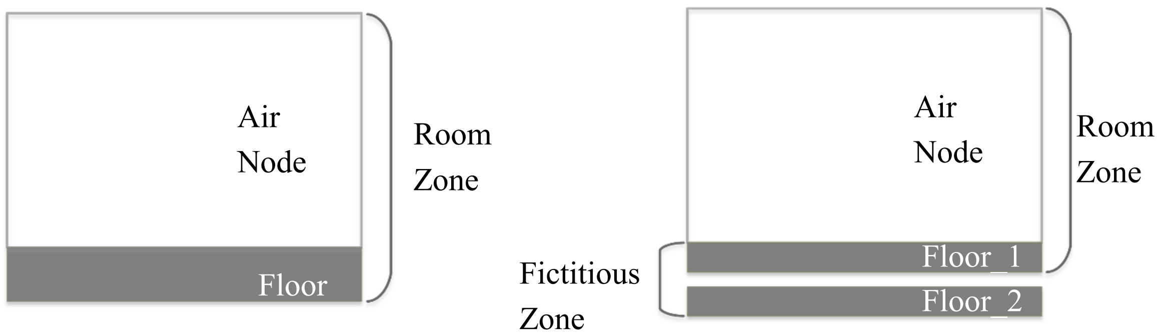


Figure 3.4. Conventional configuration of a room in TRNSYS (**left**); and configuration with the added fictitious zone in TRNSYS (**right**).

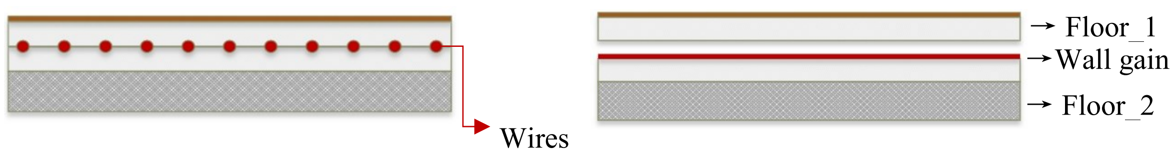


Figure 3.5. Conventional configuration of an EHF (electrically heated floors) (**left**); and configuration of the floor in TRNSYS with the added fictitious zone and the wall gain (**right**).

3.2.1.3. Model Verification

The implementation of this model is applied to the residential building presented in paragraph 3.1.1. To validate the implementation of the EHF via the *wall gain*, main considerations were to ensure that creating a new "fictitious" zone does not modify the building's behavior and that the proposed wall gain approach simulates the behavior of the EHF accurately.

To validate the integration of the fictitious zone, the *wall gain* was set to zero, and electrical baseboards were used to heat the building with the same control strategy as the one used earlier (perfect heating operating all day as function of the indoor temperature with a set-point at 21 °C). Simulations were performed for one month on the year used for building validation (January 2009), for the reference building (equipped with electrical baseboards only) and the modified one (with electrical baseboards and with the EHF structure with the *wall gain* set to 0). The energy consumption of the two heating systems were then compared by calculating the Normalized Mean Bias Error (NMBE). Details on the calculation of this statistical index are accessible on the ASHRAE Guideline 14-2014 (ASHRAE 2014).

Moreover, to verify the assumption of perfect contact between the two concrete layers, the temperature on the bottom of Floor_1 was compared to the temperature on the top of Floor_2 (see **Figure 3.5**). These temperatures are outputs of TRNSYS. The temperature difference between the upper side of Floor_2 and the lower side of Floor_1 were calculated for 10 days, and only the last eight days were analyzed (to ignore the initial condition effect).

Finally, Olsthoorn et al. (2016) modeled the same EHF using 2D finite-element analysis. Their results in terms of temperature at the heating cable level and floor surface temperature were compared to the one obtained with TRNSYS.

3.2.1.4. Ground Coupling

In the validated building, the coupling between the floor assembly and the ground was defined as *"identical"* and the coupling between walls and the ground used the *Type 77*. *Type 77* is a module that calculates ground temperature as a function of ground properties and weather information only. The *"identical"* hypothesis means that the surface temperature is equal on both sides of the assembly—an acceptable assumption for a house with basement and equipped with electric baseboards since the ground temperature is high and the indoor temperature in basement often low.

However, in the case of an EHF, losses to the ground are significant and highly dependent on the considered ground temperature. Consequently, it is important to consider the correct ground temperature to determine these losses. Therefore, the use of the more complex Type 1244 (TESS n.d.) was proposed. Contrary to *Type 77*, *Type 1244* also considers heat exchanges between the house and the ground to calculate ground temperature. Therefore, *Type 1244* would be more accurate, particularly for an EHF involving higher thermal losses to the ground. However, its complexity increases the computation time significantly.

To compare the hypotheses about ground coupling, ground temperatures below the slab of the basement were evaluated on 3 different levels of complexity:

- Hypothesis 1 *("Identical"):* there is no heat exchange between floor and ground, and ground temperatures at buried walls level are based on *Type 77* (original modeling).
- Hypothesis 2 (*Type 77*): Ground temperature is modeled with *Type 77* (considering that ground temperature depends only on soil properties, depth and weather information).

- Hypothesis 3 (*Type 1244*): Ground temperature is modeled with *Type 1244* (considering that ground temperature depends on soil properties, depth, weather information but also on heat exchanges with the house).

Two years of simulations were conducted, and only the second one was presented since results of first months depend on the initial conditions and do not consider the action of the EHF on the ground temperature.

Moreover, in order to show *Type 1244*'s ability to calculate heat exchanges between the house and the ground, a parametric study on insulation thickness was conducted on the house without basement.

To decrease computation time without considering the initial conditions, remaining studies used resulting ground temperatures of the second year of simulation from *Type 1244* instead of *Type 1244* itself.

3.2.2. TASK A.2: POTENTIAL OF AN EHF FOR LOAD-SHIFTING

Investigations are conducted to verify if the EHF configuration currently used in Québec is a good option for peak shifting, and understand the problematic consequences of using a simple night-running control strategy. To achieve this goal, two studies have been conducted:

- A parametric study on EHF layers' thickness to better understand the EHF's behavior and check if the EHF assembly may be modified to improve its performance without additional cost.
- A thermal comfort study to understand the problems of using a conventional controller for load-shifting (night-running control strategy in this study).

3.2.2.1. Parametric Study

To improve EHF performance, understanding the behavior and the importance of each layer of the assembly is essential. First, the insulation layer between the ground and the floor heating system has considerable influence on floor heating system performance. Previous studies show that compared to a conventional system, a floor heating system requires a thicker insulation layer to reduce heat losses in the ground (Cvetkovic and Bojic 2014; Weitzmann et al. 2005). The effect of concrete thickness on system performance has been studied too. With a hydronic floor heating system with concrete, Wang et al. (2014) reported the impact of the concrete layer on the performance of hydronic heating system: the floor surface temperature is higher when the concrete layer is thin.

However, the behavior of each layer of a floor heating system designed to store energy with high slab temperature variations was not thoroughly investigated. Therefore, further investigations are necessary for EHF with two objectives:

- Verify if the EHF assembly can be modified to improve performance without additional cost.
- Verify if the EHF may completely/partly shift peak demand to off-peak hours while maintaining occupants' thermal comfort.

For this parametric study, an ultimate night-running strategy (i.e. with consumption only during the night) was applied. The EHF heated from 8:00 p.m. to 6:00 a.m. at the rate of 120 W/m^2 (maximal power of the EHF). The heater was off when the Floor Surface Temperature (FST) exceeded 28 °C or when the operative temperature reached 24 °C. To study EHF discharge, the EHF was always turned off during the day.

To see the impact of insulation thickness on the bottom, of the concrete thickness below and above the wires, and of the insulation thickness on the top (between the concrete and the floor covering) on the overall performance of the EHF, each thickness was modified and studied separately. It was proposed that for the last parametric study an insulation layer be added on top of the concrete layer to investigate the possibility of storing more energy by allowing higher concrete temperatures. Simulations were performed during January 2009 (year used for the validation of the building). This parametric study was conducted only on the house without basement to simplify the problem. Results were compared with the reference case (**Figure 3.3**) corresponding to current installations in Québec. Simulation results were analyzed in terms of heating energy consumption, floor surface and room temperatures, as presented in **Table 3.2**.

Table 3.2: Studied parameters for the parametric study.

Floor Surface Temperature (FST)	Max T_{floor_surf}	Maximal FST, averaged for the month for all the rooms (°C)
	Daytime T_{floor_surf}	Daytime when the FST was at its maximal each day, averaged for the month for all the rooms. For example, 7:00 a.m. means that the maximal FST appeared generally at 7:00 a.m. every day and was decreasing after (*hh:mm*)
	T_{floor_surf} at 8:00 p.m.	FST at the end of the peak period (8:00 p.m.), averaged for the month for all the rooms (°C)
Operative Temperature	Max T_{op}	Maximal operative temperature, averaged for the month for all the rooms (°C)
	Daytime T_{op} max	Daytime when the operative temperature was at its maximal each day, averaged for the month for all the rooms. For example, 11:00 a.m. means that the maximal operative temperature appeared generally at 11:00 a.m. every day and was decreasing after (*hh:mm*)
	Daytime T_{op} < 20°C	Daytime when the operative temperature drops below 20°C each day, averaged for the month for all the rooms. For example, 8:00 p.m. means that the operative temperature was above 20 °C until 8:00 p.m. and was dropping below 20°C after (*hh:mm*)
Heating Energy Consumption	E	Heating energy consumption of the EHF for all the rooms in kWh, averaged by day (kWh/day)

3.2.2.2. Problematic Consequences of a Simple Night-Running Strategy

Results of the night-running strategy presented in 3.2.2.1 with the assembly presently employed in Québec were used to study the occupants' thermal comfort in each room. The thermal comfort provided by the EHF was estimated using the predicted percentage of dissatisfied (PPD) and the predicted mean vote (PMV) indexes (EN ISO 7730 (ISO 1994)). These values are outputs of the TRNSYS simulation. A clothing factor of 1 clo., a metabolic rate of 1.1 met and a relative air velocity of 0.1 m/s were considered. The median, minimal, maximal and (10th–90th) percentile range of the PPD and PMV were evaluated for each area of the building.

In a second phase, a control strategy enabling the heating system to be started during the afternoon in some rooms was proposed to verify its potential to decrease thermal comfort issues.

3.3. Task B: Development of a Self-Learning Controller with a Peak-Shifting Aim

This research aims to decrease heating energy consumption during peak periods while ensuring occupant's thermal comfort throughout the day. Peak, mid-peak and off-peak periods are defined as illustrated in **Figure 3.6**.

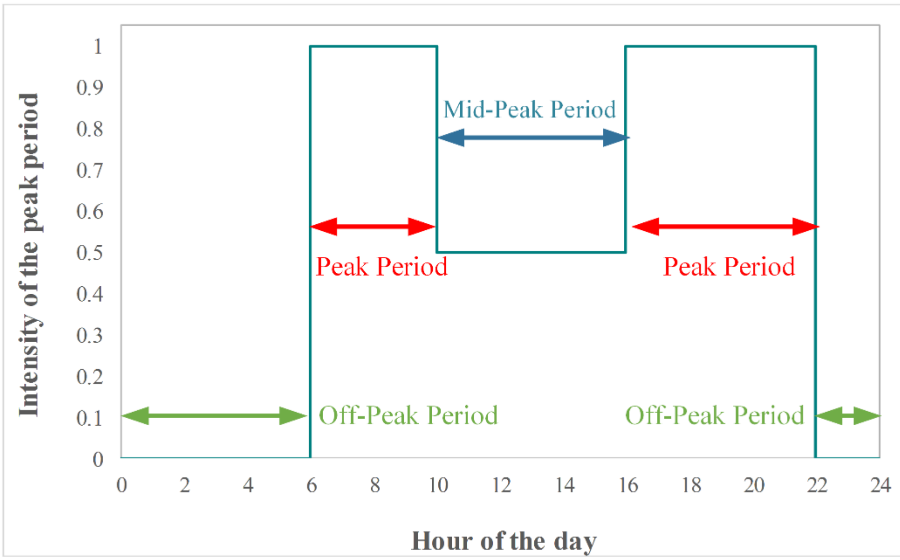


Figure 3.6: Considered peak, mid-peak and off-peak periods

Off-peak period is during the night, from 10 p.m. to 6 a.m., when there is no limit of consumption or power (apart the maximal power of the heating system, i.e. 120 W/m^2). Peak periods are from 6 a.m. to 10 a.m. and from 4 p.m. to 10 p.m., when the consumption should be as low as possible to decrease peak periods issues. Finally, the mid-peak period is during the afternoon, from 10 a.m. to 4 p.m. Even if Hydro-Québec states that this period is not, at the moment, considered as a peak period, the consumption during this period is increasing. Therefore, shifting consumption from peak periods to mid-peak hours would only modify, not solve the problem. Consequently, consumption should be shifted as much as possible from peak periods to off-peak period, and only when absolutely necessary to mid-peak period.

3.3.1. Task B.1: Development of a Weather Prediction Model

As discussed in the literature review, ambient temperature and solar radiation may impact occupants' thermal comfort significantly. However, solar radiation prediction remains difficult while hourly ambient temperature forecast is available online. Many studies have consequently focused on solar radiation predictions, but only few considered the weather conditions forecast (i.e. online information – whether it is ‘sunny’, or ‘cloudy’, etc.).

Based on historical data, Chen (1997) defined 10 levels of solar radiation with a corresponding dimensionless solar radiation for each level. The dimensionless solar radiation corresponded to the ratio between historical solar radiation and a clear sky model. Daily newspaper forecast predictions were assigned to one of the 10 defined levels to create corresponding dimensionless solar radiation value for the following day and thus calculate its total solar radiation. They tested their prediction method on 2 days, with a daily relative error of 8.1% and 4.2%. Following the same principle but using an adaptive nonlinear autoregressive with exogenous inputs (NARX) network, Tao et al. (2010) predicted the PV power for the next day. The NARX network inputs were the solar radiation for the next day assuming a clear sky and the forecasted day-type indexes. The day-type index measures forecasted weather conditions based on the same principle of dimensionless solar radiation, assuming 4 different values ranging from 0.1 to 0.9. Half-year results demonstrated an hourly error of 16.47% on the PV power production.

The technique proposed in this research develops from Chen's study (1997) based on daily weather predictions, with some modifications: automatic interpretation of weather conditions instead of manual assignment of a value; accuracy tests performed during several months instead of few days; hourly weather conditions forecast derived from Weather Networks (Environment Canada) instead of daily statements;. Most importantly, having an hourly basis allows not only the use of a controller requiring hourly data (e.g. MPC) but also the ability to apply hourly predictions to half-a-day or daily use, if necessary.

A dynamic solar prediction model is built at two different stages. First, at the training stage a correlation is developed between the weather conditions forecast (sunny, cloudy, etc.) and the actual solar radiation value. This correlation helps to develop a clearness index table. Then, during the operation stage, weather forecast is downloaded every day from the website. The correlation built in the training stage is then used to predict hourly solar radiation for the next day.

Developing a clearness index table which link clear sky solar radiation to the real solar radiation for each weather conditions forecast is advantageous: clearness value indexes can easily be checked for accuracy; clearness indexes developed in this study can be used for other applications; and weather uncertainties can be taken into consideration in simulations conveniently.

3.3.1.1. Training Stage

The training stage is presented first in **Figure 3.7**. As a function of the weather conditions, its main use is to define a clearness index representing the ratio between the hourly historical value of solar radiation and the hourly value calculated from the clear sky model. The methodology is explained more precisely in the following section.

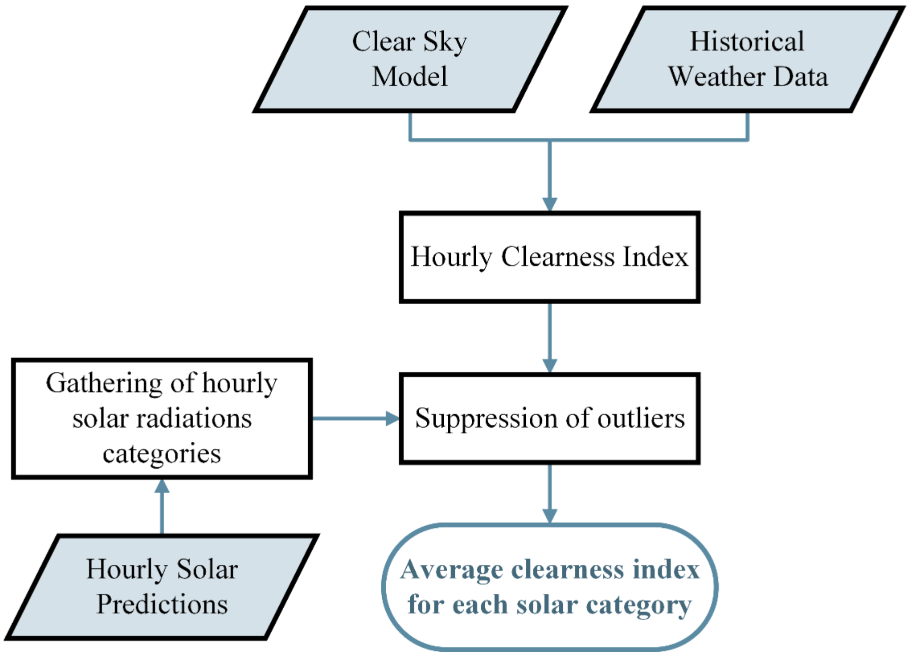


Figure 3.7: Training stage of the solar prediction model to obtain the clearness index table.

To build a clearness index table, it is first necessary to collect and calculate 3 types of data:

- **Hourly weather conditions forecast:** Hourly weather conditions forecast were gathered daily at 8 PM from Montréal's online weather predictor (Environment Canada 2016) for 127 days during April, May, August, September and October 2016. This data set was used in the solar prediction algorithm's training stage. Weather predictions from November 1st 2016 to March 31st 2017 were used in the operation stage to test the control algorithms developed.
- **Historical Weather Data**: Historical weather data was extracted from an EPW file based on records from 2016 and 2017 on the SIMEB website (LTE Hydro-Quebec 2016). Total horizontal radiation was used.
- **Clear Sky Model**: Calculations of solar radiation using the clear sky model were based on the methodology defined in ASHRAE (2009) using values presented in **Table 3.3**.

Table 3.3: Considered parameters for the Clear Sky Calculation

Parameter	**Latitude**	**Longitude**	**Altitude**	**LSM**	τ_b	τ_d
Value	45.5°C	75.6°C	0.216m	75	0.334	2.614

The hourly clearness index was then calculated using equation (3.1), excluding night data. However, the number of possible weather conditions forecast was high (55 different weather conditions were extracted from online forecasts). Since many weather conditions had less than 5 historical values, weather conditions were merged to create 12 clusters. See **Table 3.4** for resulting categories.

$$Clear\ sky\ solar\ radiation * Clearness\ Index = Historical\ solar\ radiation \tag{3.1}$$

Table 3.4: Downloaded weather conditions and resulting solar categories

Solar category number	**Solar category name**	**Weather conditions names included**	**Amount of data**
1	Sunny	Sunny – Clear	350
2	Mainly sunny	Mainly sunny	279
3	Mix	A mix of sun and cloud – A few clouds	286
4	Partly cloudy	Partly cloudy – Mainly cloudy	187
5	Cloudy	Cloudy – Cloudy. Risk of freezing drizzle – Overcast	98
6	Snow	Light snow – Snow – Ice pellets – Snow at times heavy – Periods of light snow – Periods of wet snow – Wet snow – Periods of snow – Snow at times heavy mixed with ice pellets – Snow mixed with freezing rain – Snow mixed with ice pellets – Snow mixed with rain – Light snow. Risk of freezing drizzle – Snow squalls – Periods of light snow. Risk of freezing drizzle – Snow. Risk of freezing rain. Snow and blowing snow. Snow at times heavy and blowing snow	57
7	Rain	Rain – Rain at times heavy – Freezing rain– Rain. Risk of thunderstorms – Rain. Risk of freezing rain – Periods of rain – Freezing rain mixed with rain – Freezing rain mixed with ice pellets – Periods of freezing rain	128
8	Chance of showers	Chance of showers – Chance of showers. Risk of thunderstorms – Chance of rain showers or flurries – Chance of showers. Risk of freezing rain	129
9	A few showers	A few showers – A few showers. Risk of thunderstorms	62
10	Flurries	A few rain showers or flurries – A few flurries – Chance of wet flurries – Chance of flurries – Flurries – Flurries at times heavy. Risk of snow squalls – Flurries at times heavy – Chance of flurries. Risk of freezing drizzle	32
11	Showers	Showers. Risk of thunderstorms – Showers – Showers or thunderstorms – Showers. Risk of severe thunderstorms	23
12	Drizzle	Rain or drizzle – Drizzle – Periods of drizzle – Periods of rain or drizzle – Drizzle mixes with freezing drizzle – Periods of freezing drizzle – Periods of drizzle. Risk of freezing drizzle	49

Obtained clearness indexes may become abnormally high or low given the high variability of solar radiation during the day and possible discrepancies between the clear sky model and the historical values during the sunrise and sunset periods. Therefore, the 5% highest and the 5% lowest value for each solar radiation category were excluded, totaling 10 % of discarded data.

Finally, clearness indexes were averaged for each category to create the clearness index table.

3.3.1.2. Operation Stage

During the operation stage, Montréal weather predictions are taken daily from the Environment Canada's website. Each hourly weather conditions forecast ("sunny", "cloudy", etc.) is assigned to one of 12 defined solar categories. At the same time, the total hourly horizontal solar radiation for the following day is calculated using the clear sky model. The resulting value is then multiplied for each hour by the clearness index of the selected solar category to predict the hourly amount of solar radiation.

In the simplified predictive controller proposed in this study and exposed in the following section, half-daily solar information was required to predict the time when energy should be stored. Therefore, calculated hourly solar radiation amount should be translated to half-daily solar information (i.e. in half-daily solar categories). These half-daily solar categories should transcribe the half-day's solar trend (mainly cloudy during the morning, mainly sunny during the afternoon, etc.).

Therefore, a second operation phase is required for finding a correlation between hourly solar radiation and half-daily solar categories. Predicted solar radiation was added to calculate the solar radiation for each half day. Taking the maximal and minimal value of half-daily solar radiation, half-daily solar radiation values were separated in solar categories of equal size. In the reference case, three solar categories of equal size were created.

3.3.1.3. Weather Categories

The creation of ambient temperature categories followed Cho and Zaheeruddin's work (2003). Temperature categories for the reference case were based on intervals of 5°C of the half-day's minimal temperature (e.g. if the minimal ambient temperature of the half-day is -18°C, the category [-20°C ; -15°C] is selected). Fourteen temperature categories were created taking -40°C as the minimal temperature and 30°C the maximal temperature.

In sum, the weather prediction model translates hourly values of ambient temperature and solar radiation into half-daily temperatures and solar categories: $[T^{morning};S^{morning}]$ and $[T^{afternoon};S^{afternoon}]$ with T^i being the ambient temperature category and S^i the solar category. These categories are the only information about the weather forecast considered by the controller presented in the following section. Consequently, the number of categories used influences prediction accuracy and may therefore influence controller performance too. As a result, the impact of category number on controller performance was studied.

3.3.2. Task B.2: Development of a Simplified Self-Learning Predictive Controller

A simplified self-learning predictive controller that does not require a building model is proposed in this study. Its learning process is included in the control algorithm measuring energy consumption during previous days and the building's response (minimal and maximal T_{in}). Moreover, some rules based on common sense are implemented in the algorithm to aid the learning process.

The proposed controller starts with a simple heating schedule, based on values provided in an initialization matrix $[\![E_{ini}^i]\!]$. Day by day, the learning process adjusts its energy consumption schedule to predict when and how much energy should be stored.

To maintain occupants' thermal comfort while accounting for weather uncertainties, a hierarchical structure was used. First, a high-level controller with self-learning capabilities creates an energy consumption schedule for the following day. The high-level controller includes the prediction and the scheduling of the energy consumption. Then, at each time step, a low-level controller allows the heating system to release the power proposed by the high-level controller if the indoor temperature is acceptable or force the heating system to start/stop if the indoor temperature is unacceptable.

Before detailing the control algorithm in the following parts, some rough explanations are given here to show how the controller works. Every day, the energy consumption of previous day is reported for each heating period (0:00-6:00; 10:00-12:00; 12:00-16:00 and 22:00-24:00). The heating system may be ON between [6:00-10:00] and [16:00-22:00] if T_{in} was too low the day before. Therefore, the energy consumption applied during these periods is added to the previous one. Then, the applied energy consumption is modified as a function of maximal and minimal temperatures to achieve an "idealized energy consumption" (i.e. it is reduced if T_{in} was too high or increased if T_{in} was too low). This "idealized energy consumption" is stored in a matrix per metrological information of the half-day. Having these values, the controller is able to predict the amount of energy required for storage based on the weather forecast received. This controller was implemented for each zone separately to find differences in orientation, losses to the exterior, etc.

Further details explaining the control algorithm are illustrated in **Figure 3.8**.

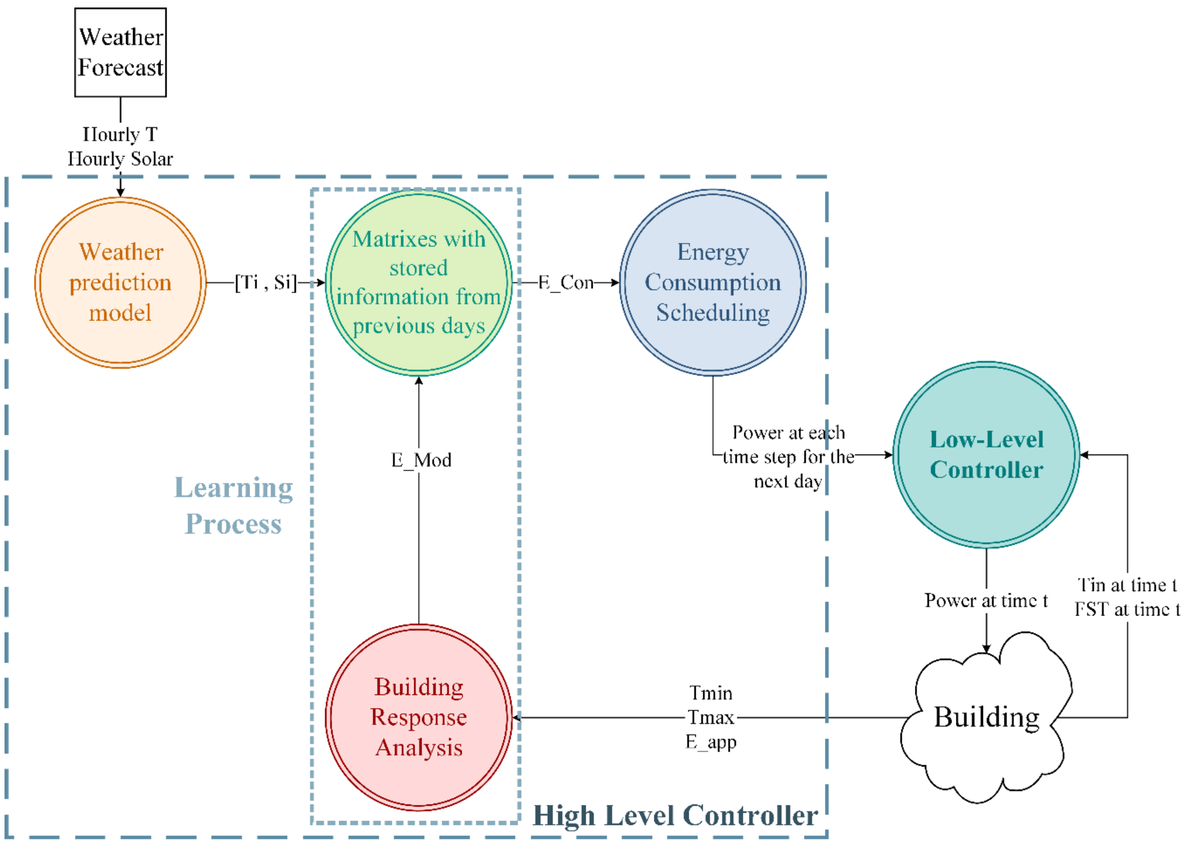


Figure 3.8: Principle of the learning control

The weather prediction model has already been explained. Therefore, the energy consumption prediction model, the scheduling model, the low-level controller and the building response analysis model will be explained separately and in more detail in the following parts.

3.3.2.1. *Energy Consumption Prediction Model*

The energy consumption prediction model is based mainly on two tables developed at the installation of the controller and updated daily:

- Table $[\![E_{mod}^{i}]\!]$ contains all modified consumption values (this term is explained later) per weather category.
- Table $[\![E_{ini}^{i}]\!]$ contains initial values. This table is used if $[\![E_{mod}^{i}]\!]$ has no historical data for the predicted weather category.

Model construction

Every day, the building response analysis model sends the energy consumption prediction model the modified heating energy consumption E_{mod}^{i}. Data is registered in the table $[\![E_{mod}^{i}]\!]$ as a function of the weather category of the previous day. An example with 2 temperature categories and 3 solar categories is given in **Table 3.5**. The table has [Temperature category * Solar Category] rows, and the number of columns increases during the learning process with the number of historical data.

Table 3.5: Example of $[\![\mathrm{E}_{\mathrm{mod}}^{\mathrm{i}}]\!]$ table

Temperature Category ($\mathrm{T^i}$)	Solar Category ($\mathrm{S^i}$)	1st Value	2nd Value
$-5 < \mathrm{T} < 0$	Sunny		
	Mid		
	Cloudy		
$-10 < \mathrm{T} < -5$	Sunny		
	Mid		
	Cloudy		

Therefore, the number of resulting categories may become high, making it time-consuming to obtain results for each category. To overcome this issue, an initialization matrix $[\![E_{ini}^{i}]\!]$ was proposed. This matrix contains values based on some expectations. During afternoon periods, energy consumption values of the initialization matrix are set to 0. During night periods, energy consumption values of the initialization matrix are calculated based on the initialization coefficient (IC) as a function of the temperature category. Considering that the coldest category has the highest power density allowed (120 W/m^2) for the entire period duration D^i (ex: for the period [0:00-6:00], $D^i = 6$), the power for each category is decreased by $(T-1)*IC$, as shown in equation (3.2).

$$E_{ini}^{i}(T) = P^{i}(T) * D^{i} = (120-(T-1)*IC)*D^{i} \qquad with\, T \in [1:14] \qquad (3.2)$$

The influence of the initialization coefficient was studied in the house without basement.

In the following days, values in the initialization matrix are updated based on historical data to decrease the discrepancy between the initial value and the desired one. Historical data does not update the initial value of its weather category. Indeed, the moment historical data for a weather category becomes available, the initialization matrix for this weather category is discarded. Therefore, historical values are used to update initial values of other weather categories.

The update principle follows logical expectations:

- At a constant solar radiation level, heating energy consumption should be lower if ambient temperature is higher and vice versa.
- At a constant ambient temperature level, heating energy consumption should be lower at higher solar radiation (higher solar category) and vice versa

The update principle is presented in Figure 3.9. $E_{mod}^{i}(T^i, S^i)$ is the previous day's historical consumption modified by the building response analysis model, with (T^i, S^i) the weather category of the day before. $E_{ini}^{i}(X, Y)$ is the initialization value calculated from equation (3.2) for the weather category (X, Y). Therefore, the controller can update some initial values after comparing the historical consumption and the initialization values of the other weather categories. These updated initial values are used only if no available historical data for the considered weather category.

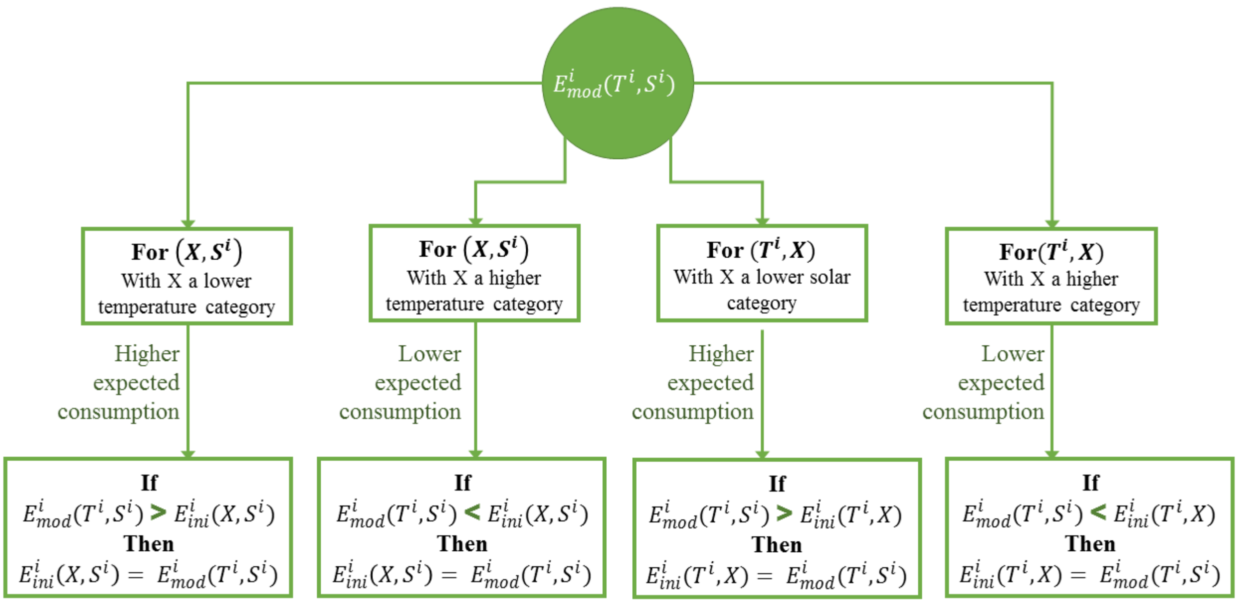


Figure 3.9: Update process of the initialization matrix.

Use of the model

When the energy consumption prediction model receives the weather forecast $[T^i, S^i]$ for the following day, the controller checks first if historical data has already been reported for this category in $[\![E^i_{mod}]\!]$. If some data has been reported, the vector $[\![E^i_{mod}(T^i, S^i)]\!]$ containing all historical data for the weather category $[T^i, S^i]$ is read. The controller calculates E^i_{con} based on the chosen prediction method (i.e. the method with which the energy demand is predicted based on stored values in $[\![E^i_{mod}[T^i; S^i]\ ]\!]$). In the first phase for this research, three simple prediction methods were tested using the maximal value; the minimal value; and the average of previous modified energy consumptions.

If data has not been reported for this weather category, the controller considers the value containing in the initialization matrix. The value E^i_{con} is then sent to the scheduling model.

3.3.2.2. Energy Consumption Scheduling

Once the energy consumption for the next day is predicted, the power is fixed to a value (80 W/m^2 during the off-peak, 10 W/m^2 during the mid-peak period). From these values, charging time is calculated for each period. If it exceeds the maximal duration for each period (e.g. the duration for the period from 0:00 to 6:00 should not be higher than 6 hours), the power during this period is increased to prevent the heating system from starting during peak periods. Also, to maintain occupants' thermal comfort even during long peak periods, the predicted energy consumption is scheduled at the end of the heating period each time. For example, if the charging duration between 0:00 and 6:00 is 4 hours, the charging starts at 2:00 to reduce losses and maintain an acceptable temperature using the stored energy only as long as possible.

3.3.2.3. Low-Level Controller

Night and afternoon heating consumption schedules are sent to the low-level controller. This algorithm is used to ensure a good thermal comfort, particularly during the first weeks of the learning process and in case of low predictions accuracy. As a result, the low-level controller receives information from the load management model and decides to implement it or not based on the current indoor temperature and the acceptable temperature range defined ($Tmax_{low-level}$ and $Tmin_{low-level}$), as presented in **Figure 3.10**.

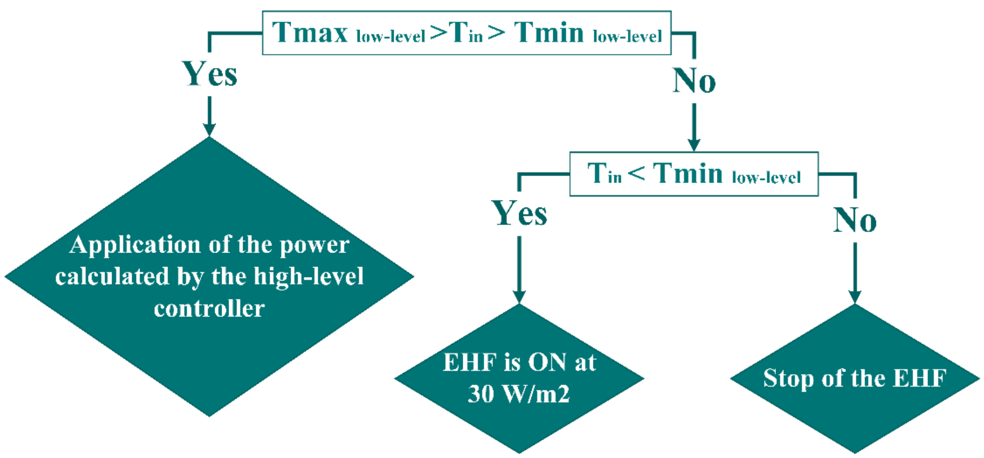


Figure 3.10: Principle of the use of the low-level controller

3.3.2.4. Building Response Analysis Model

The last part of the high-level controller is the building response analysis model. The controller is meant to verify if the amount of energy stored during the previous day was accurate, or too high or too low to improve the performance of the high-level controller. To analyze the building response, 12 terms are extracted at the end of each day:

- Maximal indoor temperature from [0:00 – 6:00], [6:00– 12:00], [12:00– 22:00] and [22:00– 24:00]

- Minimal indoor temperature from [0:00 – 6:00], [6:00– 12:00] , [12:00– 22:00] and [22:00– 24:00]
- Heating energy consumption from [0:00 – 6:00], [6:00– 12:00] , [12:00– 22:00] and [22:00– 24:00]

The learning process must respect two main objectives: decrease consumption as much as possible between [6:00 – 10:00] and [16:00 –22:00] and keep the indoor temperature at an acceptable range. To achieve that goal, a modified consumption (E^{i}_{mod}) was introduced. This modified consumption corresponds to:

- The applied consumption (without modification) if thermal comfort was met
- The consumption that would have produced a satisfying thermal comfort if poor thermal comfort. Indeed, system inertia sometimes prevents the low-level controller from maintaining an acceptable thermal comfort by itself. Therefore, to learn about the inertia of the building and adjust the recommended energy consumption, the applied consumption is modified. The methodology for modifying the historical consumption is explained in the following paragraphs using equations (3.3) and (3.4).

To measure thermal comfort satisfaction, a range of acceptable temperatures is defined and limited by $Tmax_{learning\ process}$ and $Tmin_{learning\ process}$. In this study, a parametric analysis was conducted to select the best value for obtaining the best thermal comfort possible during the day (measured with the PPD). For future implementations, these values may be modified following occupants' thermal comfort preferences.

As shown in equations (3.3) and (3.4), the energy consumption applied is modified depending on the difference between the maximal/minimal temperature that should not be exceeded/undershot and the maximal/minimal temperature that has been observed. Moreover, the speed and magnitude of the learning process are defined by the building response learning (BRL) coefficient (i.e. it defines the increase or decrease in applied energy consumption when some thermal comfort issues appeared). A parametric study on BRL's influence on controller performance was conducted. The modification of the historical consumption is limited in order to have $\frac{E^{i}_{applied}}{2} \leq E^{i}_{mod} \leq 2 * E^{i}_{applied}$.

$$E_{mod}^{i} = E_{applied}^{i} * \min\left(2{,}1 + \frac{BRL * \left(Tmin_{learning\ process} - Tmin^{i}\right)}{5}\right) \tag{3.3}$$

$$E_{mod}^{i} = E_{applied}^{i} * \max\left(\frac{1}{2}, 1 - \frac{BRL * \left(Tmax^{i} - Tmax_{learning\ process}\right)}{5}\right) \tag{3.4}$$

The principle of the building response analysis is illustrated in **Figure 3.11** (analysis of resulting temperatures during the previous night and morning) and **Figure 3.12** (analysis of resulting temperatures during previous afternoon and evening).

The night analysis is performed first to adjust night consumption. The scope of the night analysis is two-fold: the night consumption should be increased if the indoor temperature is too high and decreased if the indoor temperature is too low. The principle of the building response analysis is illustrated in **Figure 3.11**. In this figure, $Tmax_{[X\text{-}Y]}$ and $Tmin_{[X\text{-}Y]}$ correspond respectively to the maximal and minimal temperature during a time period [X:00 ; Y:00]. Due to building thermal inertia, the minimal temperature between [6:00-12:00] is not verified if the indoor temperature of the building is already too hot between [0:00-6:00].

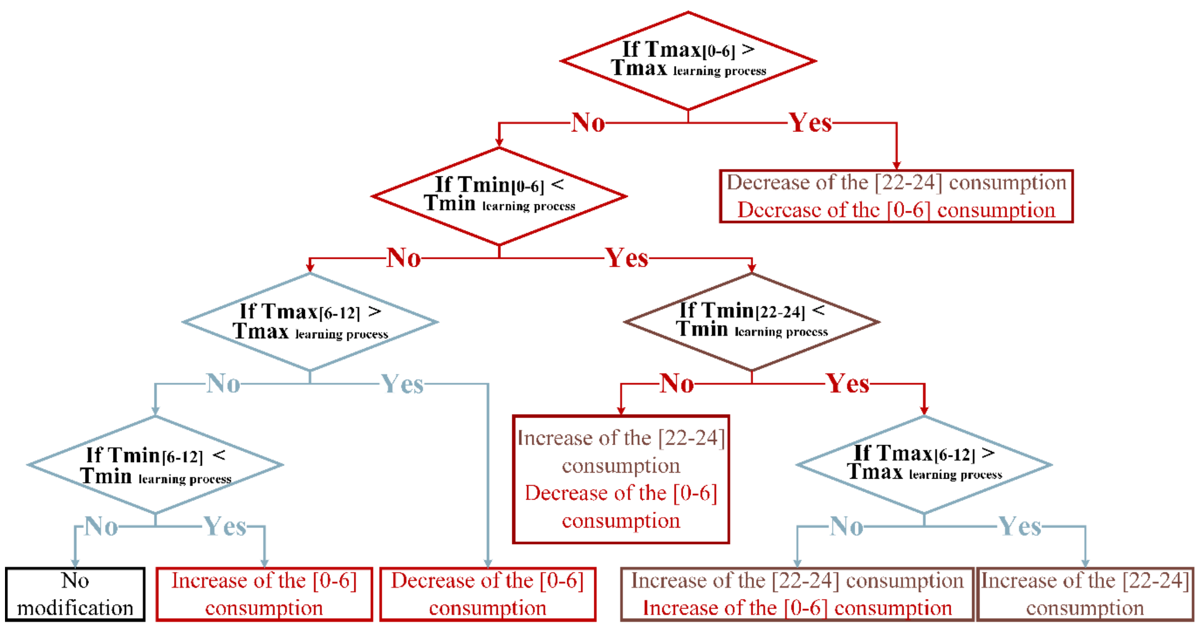


Figure 3.11: Analysis of the temperatures between [0:00-6:00] and [6:00-12:00] to calculate the modified consumption of the day before.

Over a second phase, the response of the building during the afternoon and evening is analyzed. The objective is the same as for the night analysis: increasing the energy consumption during previous periods of an under-heating and decreasing the energy consumption during previous periods of an over-heating.

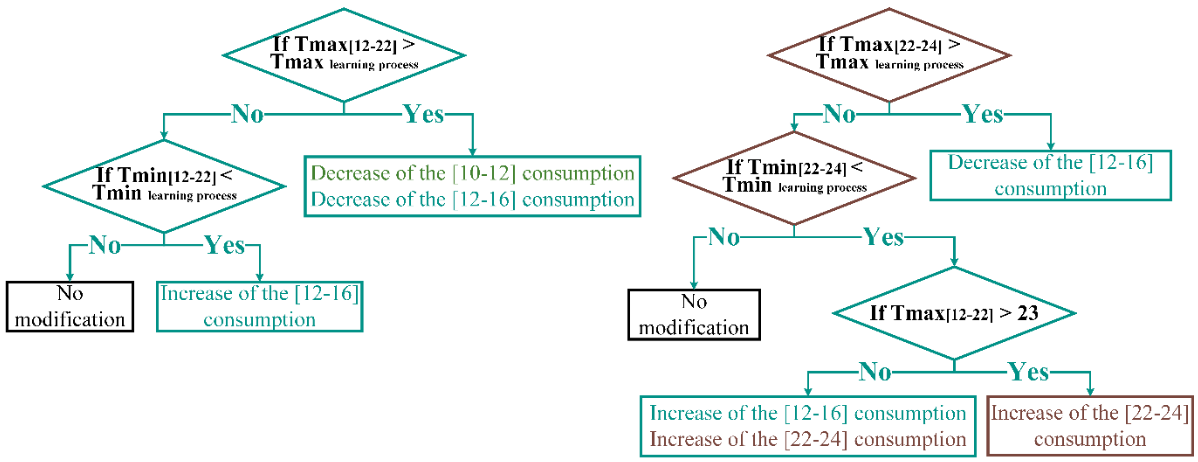


Figure 3.12: Analysis of the temperatures between [12:00-22:00] and [22:00-24:00] to calculate the modified consumption of the day before.

3.3.2.5. TRNSYS Implementation of the Controller

Coupling of TRNSYS and Matlab

TRNSYS, like many energy simulation software, does not currently propose sufficient tools to easily implement control algorithms in the software. As a result, the implementation has been realized by linking TRNSYS and Matlab with *Type 155*, which allows them to communicate at every time step.

To communicate, Matlab receives some inputs from TRNSYS: current room air and floor surface temperatures in each zone, day of the year and hour of the day (extracted from the *Type 95a*), and the power applied in the previous time step in each zone. With this information, the Matlab algorithm calculates the power that should be applied for the next time step for each zone and send it back to TRNSYS.

For security reasons, it was decided to implement part of the low-level controller directly into TRNSYS. Therefore, before applying the power sent from Matlab to TRNSYS for each room, TRNSYS checks if room air temperature or the floor surface temperature is too high. It was also possible to write this instruction directly in Matlab, but to avoid a surge in heating cable temperature in the case of a problem in the Matlab algorithm, this instruction was set directly into TRNSYS.

Weather Forecast Predictions

The weather forecast was downloaded daily from Environment Canada, but these predictions were not implemented directly in the control algorithm. Translating the weather forecast to the solar category and temperature category number requires no information from the building.

Therefore, to reduce the high computation time arising from the coupling between TRNSYS and Matlab, weather categories for each half day were directly set as inputs of the Matlab algorithm.

3.3.3. TASK B.3: PARAMETRIC STUDIES OF THE PARAMETERS OF THE SELF-LEARNING CONTROLLER

A parametric study was conducted on several parameters in the control algorithm and a review of these is presented with the value chosen for the reference case and the other testes values:

- **The prediction method** is the method that predicts the energy consumption based on stored values in $[\![E^i_{mod}[T^i; S^i]\,]\!]$. Selection of the maximal, minimal, or average value of previous demands is tested. The reference case is the selection of the maximal value.
- **The building response learning (BRL) coefficient** defines the increase or decrease in applied energy consumption when some thermal comfort issues appeared. For instance, a BRL coefficient of 1 with a temperature difference of 1 degree corresponds to a 20% increase or decrease in consumption (equations (3.3 and (3.4). The reference case is set to 1. Tested values range from 0 to 2 with a 0.2 step.
- $\boldsymbol{Tmax_{learning\ process}}$ and $\boldsymbol{Tmin_{learning\ process}}$ are the maximal/minimal temperature used for the learning process. Therefore, if T_{in} exceeds $Tmax_{learning\ process}$ or if T_{in} goes below $Tmin_{learning\ process}$, the applied consumption will be decreased or increased respectively before being stored in $[\![E^i_{mod}[T^i; S^i]\,]\!]$. The reference case is set to 24 and 21 and tested values are [23 ; 25] and [20 ; 22] with a 0.5 step respectively for the maximal and minimal temperatures.
- $\boldsymbol{Tmax_{low-level}}$ and $\boldsymbol{Tmin_{low-level}}$: The low-level controller stops/starts the heating system when T_{in} reaches $Tmax_{low-level}$ or if it goes below $Tmin_{low-level}$. The reference case is set to 23 and 21 respectively for the maximal and minimal temperatures. Testes values are [22 ; 24] and [20 ; 22] respectively for the maximal and minimal temperatures with a 0.5 step.

- **Initialization coefficient (IC):** The initialization is created based on the temperature category as shown in equation (3.2). The reference case is set to 10. Tested values are from 5 to 15 with a 2.5 step.

Variations in average power during peak period, average power during mid-peak period and time per day with a PPD ≥ 10 % are presented. Simulations were performed on the house without basement from the 1st of November 2016 to 31st of January 2017.

3.3.4. TASK B.4: COMPARISON OF CONTROLLERS

Two non-predictive controller types meant to define some baseline for further comparison are proposed.

- Control C1 is a simple two powers controller without any shift in peak demand. The EHF is heated at 40 W/m^2 when the room air temperature (T_{in}) is lower than 21.5 °C and heated at 80 W/m^2 when $T_{in} < 20.5$ °C.
- Control C2 is a non-predictive controller meant to shift peak demand. The developed non-predictive strategy C2 is based on an algorithm that selects the system power with the following parameters: on-peak/off-peak/mid-peak periods, room air and floor surface temperatures. Since it has been reported that occupants may experience thermal comfort issues with a complete night-control strategy, two scenarios are proposed in this study (see **Figure 3.13**): 1) the peak-shifting control strategy aims to completely shift the peak periods but uses the mid-peak to partly recharge the system; and 2) the night-running control strategy aims to heat only at night.

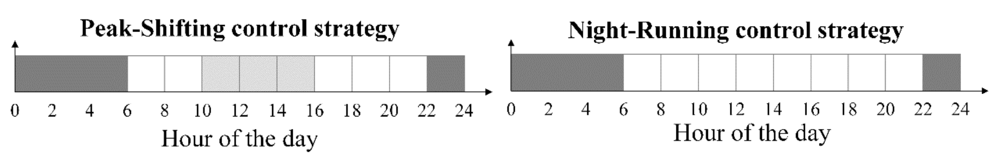


Figure 3.13: Heating schedules of the non-predictive control for load management

- During off-peak periods (black portion in **Figure 3.13**), the EHF heats at maximal power density (120 W/m^2). EHF is off if $F_{ST} \geq 28$°C or $T_{in} \geq 23$°C.
- During on-peak hours, (white in **Figure 3.13**), the EHF is off. It is on only if $T_{in} \leq 20$°C at a lower power density (20 W/m^2).

- Finally, during mid-peak hours, the EHF is on at 30 W/m^2 if $T_{in} \leq 21.5°C$ for the peak-shifting control strategy (in gray in **Figure 3.13**).

The 4 proposed controllers (C1; C2 – Peak Shifting; C2 – Night Running; Self-Learning) were compared in terms of average power during the peak and mid-peak period, and thermal comfort. All simulations were conducted from November 1 2016 to March 31 2017 on both buildings (with and without basement).

Average powers applied were calculated for the whole house. Average powers are the addition of average powers of each room of the building, including basement and first floor for the house with basement. The thermal comfort was evaluated based on discomfort per day. The time of discomfort per day is estimated based on time duration with a PPD higher than 10% according to ASHRAE (ASHRAE 2013) using equation (3.5). Every day, the period with a PPD exceeding 10% was calculated for each room ($Discomfort_d^r$) and these values were added for the N days of the simulation. Finally, a weighted factor representing the percentage of the area considered from the building was taken into consideration and the result was divided by the number of days to obtain the average value of daily discomfort.

$$Discomfort = \sum_{r=1}^{R} \frac{\left[\sum_{d=1}^{N} (Discomfort_d^r) * \frac{Area^r}{Total\ Area}\right]}{N} \tag{3.5}$$

For the house with basement, only basement rooms were considered in the comfort equation. The first floor has not been modified and still uses a perfect heating system maintaining a defined constant set-point. Therefore, the thermal comfort was not modified on the first floor by the supervisory controller used in the basement.

Moreover, a financial analysis from the occupant's and supplier's point of view was conducted. To be implemented on a large scale in residential buildings, the controller has to be an advantage, or at least not an inconvenient, for the owner. This may be measured with a Time-of-Use or Real-time electricity Tariff, which does not exist in Québec at the moment. Therefore, using EHF to shift the consumption from peak to off-peak periods cannot be an advantage in Québec since the total energy consumption increases with the rise of slab temperature when an EHF is used for a peak-shifting aim. However, this kind of tariff exists in other provinces and countries and is planned to be implemented from winter 2018/2019 in Québec (Rettino-Parazelli 2017). Therefore, a financial study was conducted using Ontarian electricity prices (see **Table 3.6**), the province just next to Québec. The weekly cost with each studied control strategy were compared for the period from November 1st 2016 to March 31st 2017.

Table 3.6: Time-of-use electricity prices in Ontario (HydroOne 2017)

	Peak period	Mid-Peak Period	Off-Peak Period
Price during weekdays (¢/kWh)	18	13.2	8.7
Price during weekends (¢/kWh)	8.7	8.7	8.7

Besides that, during high peak periods, the supplier buys electricity from other countries in order to match the demand. However, during these periods, most of them have the same peak problems, selling the electricity at a higher price. In Québec, the supplier purchases the electricity at the rate of \$20 per kW during peak period and will purchase it at \$108 per kW from winter 2018/2019 (Hydro-Québec Distribution 2016). Therefore, to study the potential savings for the supplier, days with an average ambient temperature below -15°C were extracted during the considered period (from November 1st to March 31st). During these days, average supplied power during peak periods of the C2 and self-learning controllers were compared with the average supplied power during peak periods of the C1 controller in order to calculate the avoided cost per year and per building.

3.4. Summary

To develop a low-cost solution for EHF that would decrease the heating energy consumption during the peak periods, it was first necessary to model the EHF in TRNSYS. A solution for creating a fictitious zone that would insert a surface heat flux inside the floor assembly was proposed. Some parametric studies on the layer's thickness and a thermal comfort study for a better understanding of EHF behavior and issues of a non-predictive control for a peak-shifting aim were also proposed.

Over a second phase, a solar prediction model and a self-learning predictive controller were developed. The solar prediction model is based on a clearness index table linking weather conditions forecast from Environment Canada to predict solar radiation amount. The simplified self-learning controller adjust day after day the stored amount of energy as a function of the predicted weather forecast of the day after. The learning process is realized based on the previous heating energy consumption and the response of the building. Moreover, some parametric studies are proposed on some parameters of the self-learning controller in order to understand the behavior of the controller and to choose the best value. Finally, performance of the controllers in terms of consumption, thermal comfort and energy cost are compared to some non-predictive controllers.

CHAPTER 4: RESULTS

4.1. TASK A: STUDY OF AN EHF IN TRNSYS WITH A LOAD-SHIFTING AIM

4.1.1. TASK A.1: MODELING OF AN EHF IN TRNSYS

4.1.1.1. Model Verification

Some verifications have been done to verify that the validated building model was not corrupted by the EHF implementation.

First, the energy demand of the building with and without EHF was compared. A monthly NMBE of 0.20 % and an hourly NMBE of 1.91 % were calculated, what is acceptable according to the ASHRAE Guideline.

Moreover, to verify the EHF implementation, surface temperatures inside the "fictitious" zone has to be equal. Therefore, the temperature difference between the upper side of Floor_2 and the lower side of Floor_1 are calculated for 10 days, and only the last eight days are taken for analysis (to ignore the initial condition effect): results showed a NMBE of less than 1%.

Finally, results in terms of heating cable temperature and floor surface temperature are compared with results using a 2D finite-element developed by Olsthoorn et al. (2016). Their results are very close to the 1D TRNSYS model results: the predicted temperature at the heating cable height from the TRNSYS model was 32.38 °C, when the average temperature on the 2D model of was 31.11 °C. Similarly, results of the 2D model show a difference in the floor surface temperature in comparison with the TRNSYS model of approximately 1 °C. Moreover, the hypothesis of an isothermal floor surface was validated.

4.1.1.2. Impact on the Ground Coupling Hypothesis

To study the differences between the presented ground coupling hypotheses, ground temperature below the slab of the basement are compared considering 3 different levels of complexity. Resulted ground temperatures at the floor basement level (i.e. just below the slab) are presented in **Figure 4.1**. Ground temperatures of the walls are not presented here.

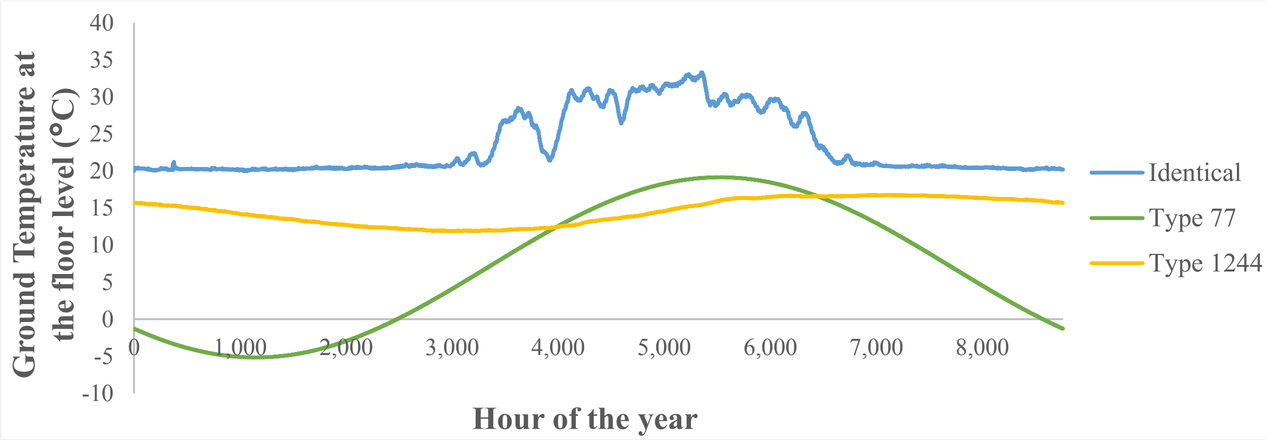


Figure 4.1: Ground temperature below the basement as a function of the hypothesis

As shown in **Figure 4.1**, the *identical* scenario provides a ground temperature equal to the indoor temperature. Compared to *Type 77*, *Type 1244* gives a higher ground temperature during winter. Indeed, *Type 1244* considers the heat exchange between the slab and the ground. Therefore, the ground temperature calculated using *Type 1244* considers the heating of the ground by the EHF. Therefore, after a certain period, the ground temperature is higher and losses to the ground become lower. These differences in ground temperature greatly affect the energy consumption as shown in **Table 4.1**. Therefore, in the rest of the research, the ground coupling is implemented using resulting ground temperatures calculated *Type 1244* for the floor of the basement and for the buried walls.

Table 4.1: Comparison of energy consumption during the year for the 3 hypotheses

	Energy consumption during the year (kWh)	**Difference in energy consumption compared to Type 1244**
Hypothesis 1 - Identical	13705	7%
Hypothesis 2 - Type 77	17003	32%
Hypothesis 3 - Type 1244	12860	

4.1.1.3. Impact on the Insulation Thickness on the Ground Temperature

As explained previously, the *Type 1244* has the faculty to consider heat exchanges between the house and the ground. To deeper illustrate that a parametric study is conducted on the house without basement to study the influence of the insulation thickness on the resulting ground temperature.

These results, as function of the insulation thickness on the bottom, are presented in **Figure 4.2** for the building without basement. They show that the floor heating system heats the surrounding ground, particularly when the insulation thickness is low. The temperature difference during winter may be quite high (5°C difference between 7.5cm and 20cm), i.e. involving a significant difference in energy consumption. Therefore, the use of the *Type 1244* is particularly important on studies with floor heating system.

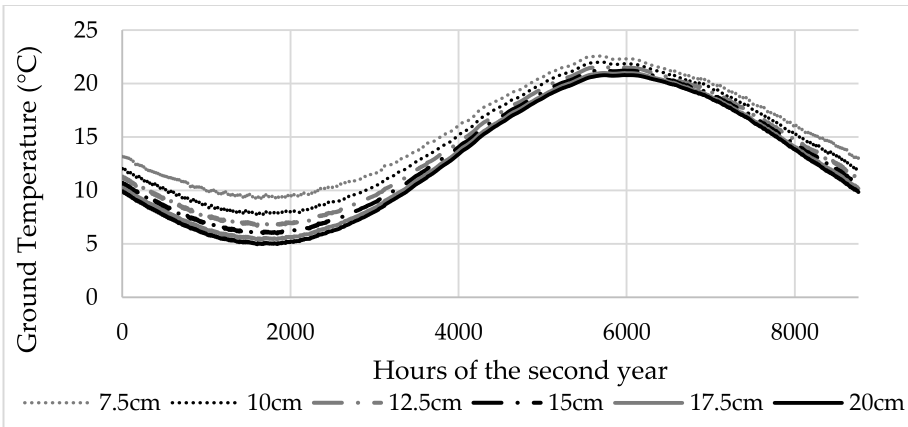


Figure 4.2: Ground temperature below the building without basement as a function of the insulation thickness on the bottom.

4.1.2. Task A.2: Study of the Potential of an EHF for Load Shifting

Impact of the EHF layers thickness on the resulting FST and operative temperature during the day is studied to improve the understanding of the behavior of the EHF and check if the current used assembly is suitable for a peak-shifting application. Moreover, the occupants' thermal comfort is studied room per room to have a better understanding of the issues of a non-predictive control for EHF. All these studies are conducted on the house without basement.

4.1.2.1. Impact of the EHF Layers Thicknesses

Insulation on the Bottom

Table 4.2 shows that the maximal FST, the FST at 8:00 p.m., and the maximal operative temperature increase as a function of the insulation thickness. With the increase of the insulation thickness, heat loss to the ground decreases: a higher proportion of the heat flux ends up in the room resulting in an increase in the maximal FST and the operative air temperature. For that same reason, the maximal FST and operative air temperature appear earlier, and the operative temperature stays above 20°C for a longer period. Finally, the energy consumption decreases significantly as the insulation thickness increases. Hence, a thicker layer of insulation between the ground and the concrete layer is desirable for an EHF.

Table 4.2: Parametric study - Impact of the lower layer insulation thickness.

Thickness of Insulation on the Bottom (m)	**FST**			**Operative Temperature**			**E (kWh/ Day)**
	Max T_{floor_surf} (°C)	Daytime T_{floor_surf} Max $(h\!:m)$	T_{floor_surf} at 8:00 pm (°C)	Max T_{op} (°C)	Daytime T_{op} Max $(h\!:m)$	Daytime $T_{op} < 20$ °C $(h\!:m)$	
0.075	28.02	6:33 am	23.64	23.08	10:52 am	10:25 pm	102.88
0.100 Reference case	28.16	6:19 am	23.85	23.22	10:39 am	10:50 pm	98.71
0.125	28.22	6:03 am	23.99	23.30	10:34 am	10:59 pm	95.78
0.150	28.28	6:01 am	24.09	23.36	10:28 am	11:09 pm	93.56
0.175	28.30	5:53 am	24.17	23.41	10:24 am	11:15 pm	91.86
0.200	28.33	5:48 am	24.24	23.44	10:25 am	11:20 pm	90.53

Concrete on the Bottom

Table 4.3 shows that several parameters (Daytime of the T_{floor_surf} max, FST-at-8:00 p.m., daytime of operative temperature above 20 °C, the energy consumption and the maximal operative temperature) can be considered as constant between 8 and 14 cm of concrete on the bottom of the EHF (with a constant 10 cm of concrete on the top of the EHF). Thus, having a concrete thickness below the EHF higher than 8 cm (total concrete thickness of 18 cm) does not improve the performance of the thickness.

Table 4.3: Parametric study - Impact of the lower layer concrete thickness.

Thickness of Concrete on the Bottom (m)	**FST**			**Operative Temperature**			**E (kWh/ Day)**
	Max T_{floor_surf} (°C)	Daytime T_{floor_surf} Max $(h\!:m)$	T_{floor_surf} at 8:00 pm (°C)	Max T_{op} (°C)	Daytime T_{op} Max $(h\!:m)$	Daytime $T_{op} < 22$ °C $(h\!:m)$	
0.02 Reference Case	28.16	6:19 am	23.85	23.22	10:39 am	10:50 pm	98.71
0.04	28.23	7:15 am	24.75	23.50	11:39 am	11:30 pm	100.21
0.06	28.21	7:57 am	25.34	23.65	11:59 am	11:41 pm	101.17
0.08	28.15	8:26 am	25.70	23.71	12:11 am	11:46 pm	101.79
0.10	28.04	8:29 am	25.88	23.69	12:13 am	11:47 pm	102.08
0.12	27.95	8:25 am	25.98	23.66	11:52 am	11:48 pm	102.04
0.14	27.89	8:19 am	26.04	23.64	11:43 am	11:49 pm	102.01

Table 4.3 also indicates that between concrete thickness of 2 and 8 cm on the bottom, the maximal FST decreases while the FST-at-8:00 p.m. increases, the maximal FST and operative temperature appear later, and the duration with a good thermal comfort is extended: the storage capacity has

increased. Thus, between 2 and 8 cm of concrete on the bottom, one can observe a slight improvement of the performance of the system (for example, the period with an operative temperature staying above 20 °C is increased of more than one hour). This is due to an increase of the storage capacity of the system. Thus, one can conclude that a small increase of the concrete thickness increases the storage capacity, and thus provides the required thermal comfort for a longer period.

Concrete on the Top

Further simulations were performed to investigate the impact of the thickness of the upper (screed) layer of concrete on the thermal behavior of the building. **Table 4.4** shows that as the concrete thickness on the top increases, the maximal operative temperature and the FST-at-8:00 p.m. increase. Moreover, the maximal FST, the maximal operative temperature and the drop of the operative temperature above 20 °C appears significantly later. In fact, with the increase of the concrete thickness, a higher amount of energy is stored and released. Finally, the increase of the concrete thickness increases the energy consumption until provide enough energy to have an acceptable thermal comfort (operative temperature higher than 20 °C until the end of the peak period from 6 cm of concrete). In summary, the screed layer thickness has an important effect on the EHF performance. It allows more energy to be stored thus provides a longer period of acceptable thermal comfort for the occupants.

Table 4.4: Parametric study - Impact of the top layer concrete thickness.

Thickness of concrete on the top (m)	**FST**			**Operative Temperature**			**E (kWh/ Day)**
	Max T_{floor_surf} (°C)	Daytime T_{floor_surf} max $(h:m)$	T_{floor_surf} at 8:00 pm (°C)	Max T_{op} (°C)	Daytime T_{op} max $(h:m)$	Daytime $T_{op} < 20$ °C $(h:m)$	
0.02	28.46	4:12 am	19.02	22.46	7:56 am	3:52 pm	90.54
0.04	28.21	4:37 am	20.82	22.67	8:54 am	6:28 pm	93.41
0.06	28.12	4:44 am	22.09	22.85	9:33 am	8:29 pm	95.49
0.08	28.13	5:31 am	23.05	23.02	10:13 am	10:01 pm	97.18
0.10 Reference Case	28.16	6:19 am	23.85	23.22	10:39 am	10:50 pm	98.71
0.12	28.21	7:04 am	24.58	23.43	11:25 am	11:21 pm	100.15
0.14	28.26	7:50 am	25.20	23.61	11:48 am	11:37 pm	101.79

To compare the two concrete layers, the case with 4 cm of concrete on the bottom (and 10 cm on the top) and the case with 12 cm of concrete on the top (and 2 cm of concrete on the bottom) are compared. The results are really close. Thus, the concrete thickness has a significant impact on the performance but not the position of the concrete regarding the EHF.

Insulation on the Top

In this part, a thin layer of insulation on the top (between the concrete and the floor covering) is considered to study the possibility to increase the concrete temperature. **Table 4.5** shows a decrease of the maximal FST, the maximal operative temperature, and the duration over the day with an operative temperature above 20 °C when the thickness of the insulation is increased. In addition, the electrical energy consumption increases with the insulation thickness. This is mainly because as insulation thickness on the top increases, the proportion of heat loss to the ground increases. Thus, the occupants' thermal comfort decreases significantly. **Table 4.5** also shows that the electrical energy consumption does not increase between 4 and 5 cm, because the EHF has been already 100% charged during the night.

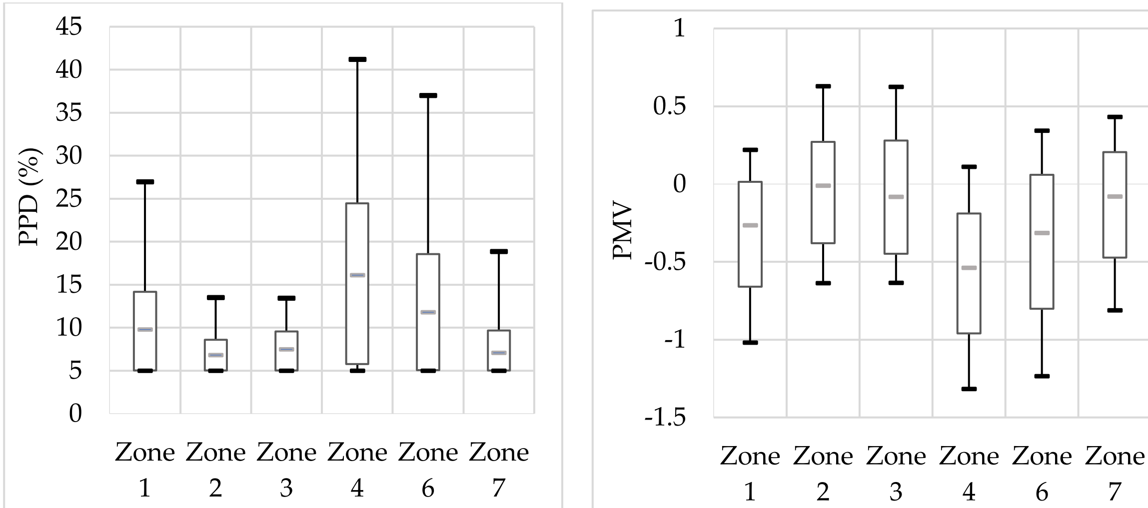
Table 4.5: Parametric study - Impact of the top layer insulation thickness.

Thickness of Insulation on the Top (m)	**FST**			**Operative Temperature**			**E (kWh/day)**
	Max T_{floor_surf} (°C)	Daytime T_{floor_surf} Max $(h\!:\!m)$	T_{floor_surf} at 8:00 pm (°C)	Max T_{op} (°C)	Daytime T_{op} Max $(h\!:\!m)$	Daytime $T_{op} < 20$ °C $(h\!:\!m)$	
0 Reference Case	28.16	6:19 am	23.85	23.22	10:39 am	10:50 pm	98.71
0.01	27.39	9:31 am	25.14	23.13	12:14 am	10:35 pm	107.60
0.02	26.07	11:01 am	24.39	22.15	12:03 am	10:40 pm	110.41
0.03	25.06	11:11 am	23.61	21.31	12:17 am	6:53 pm	113.39
0.04	23.73	11:46 am	22.46	20.17	12:01 am	8:07 pm	116.20
0.05	22.31	12:09 am	21.13	18.93	11:59 am	-	117.91

4.1.2.2. Issues of a Non-Predictive Control for Load Management

Total Night-Control Strategy

To have a better understanding of the occupants' thermal comfort issues with a total night-control strategy, PPD and PMV are studied for the reference case (**Figure 3.3**). The total night-control strategy was presented in paragraph 3.2.2.1. It consists to heat during the night at the maximal power. The EHF is OFF when the FST or the room air temperature reaches a certain temperature, and is OFF during all day whatever the room air temperature is. To visualize the results, **Figure 4.3** shows the minimal and maximal (black limits), the median (in grey) and the 10th and 90th percentile (the box) for PMV and PPD.



(**a**) (**b**)

Figure 4.3: Median, minimal, maximal and (10th–90th) percentiles of: (a) the PPD; and (b) the PMV for each zone for the month of January with the total night-control strategy.

Figure 4.3a, showing the PPD results, allows to observe important differences between zones. The zone facing south (Zone 2) and zones with low thermal losses keep an acceptable thermal comfort (90th percentile below 10%). However, zones 1, 4 and 6 have some comfort issues. To understand these results, PMV are presented in **Figure 4.3**b. Results show that the dissatisfaction in zones 1, 4 and 6 is due to an under-heating of these zones (PMV almost always negative, and sometimes below −1). Moreover, in the zones facing south (2 and 3), a slight over-heating may be observed.

Thus, the thermal comfort is not acceptable in all zones with a night-running strategy. Thus, to ensure the thermal comfort of occupants in these zones, allowing the EHF to heat during the day in these zones is obligatory.

Partial Night-Control Strategy

The system is now allowed to heat zones 1, 4 and 6 when their operative temperature is below 23 °C between 9:30 a.m. and 4:00 p.m. Results in terms of thermal comfort are presented in **Figure 4.4**.

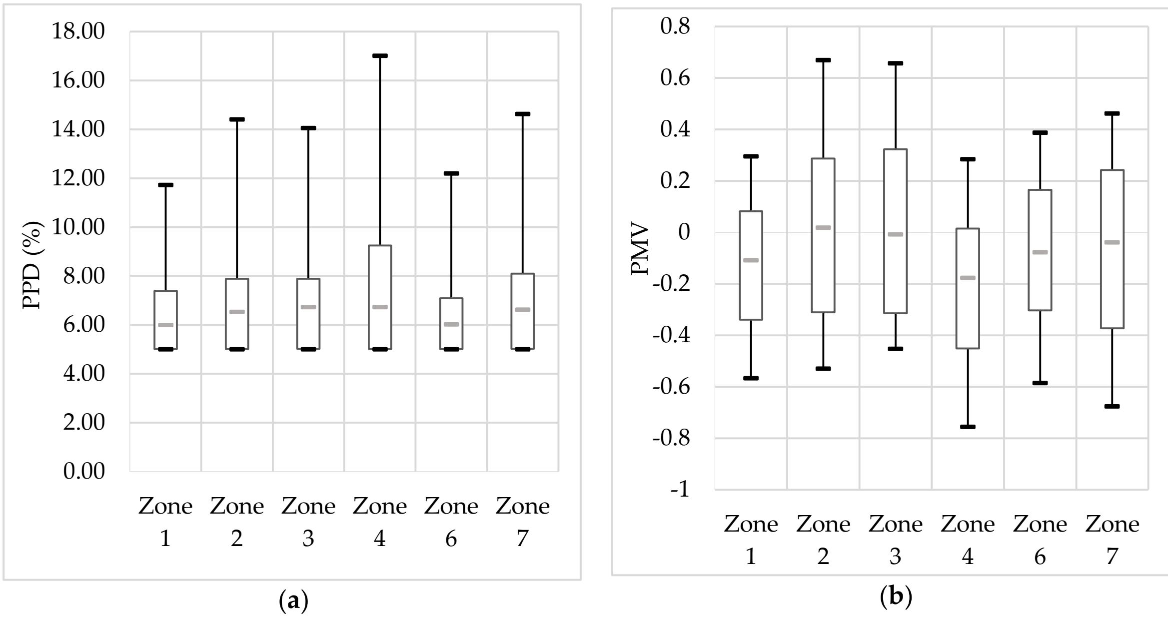


Figure 4.4: Median, minimal, maximal and (10th–90th) percentiles of: (a) the PPD; and (b) the PMV for each zone for the month of January with the partial night-control strategy.

Figure 4.4 shows that the 90th percentile of the PPD stays below 10% for all the zones. Moreover, the (10th–90th) percentiles range of the PMV stay between −0.5 and 0.5 in all the zones. Thus, it can be concluded that the thermal comfort of this system is acceptable for occupants.

The possibility of heating between 9:30 a.m. and 4:00 p.m. in three zones lead to 84% of the total energy consumption during the night and 16% between 9:30 a.m. and 4:00 p.m. (with a total energy consumption per day of 99.68 kWh).

Therefore, the thermal comfort study showed that a complete night-control strategy was not possible in half of the zones (depending on the amount of external walls and their orientation). Nevertheless, it was proved that an acceptable thermal comfort was achieved with only 16% of the energy consumption during the day (only between 9:30 a.m. and 4:00 p.m.).

However, results show an over-heating of some zones at some times during the day. In fact, the stored energy amount is not always required, involving over-heating, especially in the zones facing the south. Then, using a different control strategy, which takes into consideration the amount of energy required for the next day in conjunction with the weather prediction, is required to improve the thermal comfort.

As a result, these preliminary results allow to have a better understanding of the behavior of the EHF. Moreover, it showed the importance of the control strategy and especially of the necessity to use weather predictions to ensure occupants' thermal comfort.

Before presenting the results of the proposed simplified self-learning controller, considering weather forecast into account but with a low implementation cost, the accuracy of the proposed solar prediction model is presented in the following section.

4.2. Task B: Self-Learning Controller with a Peak-Shifting Aim

4.2.1. Task B.1: Solar Predictions Model

As explained in the paragraph 3.3.1, a training stage is required in order to create the clearness indexes table that will be used in the operation stage. The resulted clearness index table for Montreal is presented in **Table 4.6**. Obtained values of clearness indexes are consistent with values that may be expected; the index for the sunny category is close to 1, and values for snow and rain are particularly low.

Table 4.6: Clearness indexes table for Montreal

Category	Sunny	Mainly sunny	Mix sun/cloud	Flurries	Cloudy	Snow
Clearness index	0.81	0.74	0.66	0.47	0.46	0.17
Category	Rain	Partly cloudy	Chance of showers	Few showers	Showers	Drizzle
Clearness index	0.14	0.47	0.45	0.34	0.35	0.45

In order to study the accuracy of the model, **Figure 4.5** presents the historical and predicted solar radiation from the developed model from November 1st 2016 to January 31st 2017.

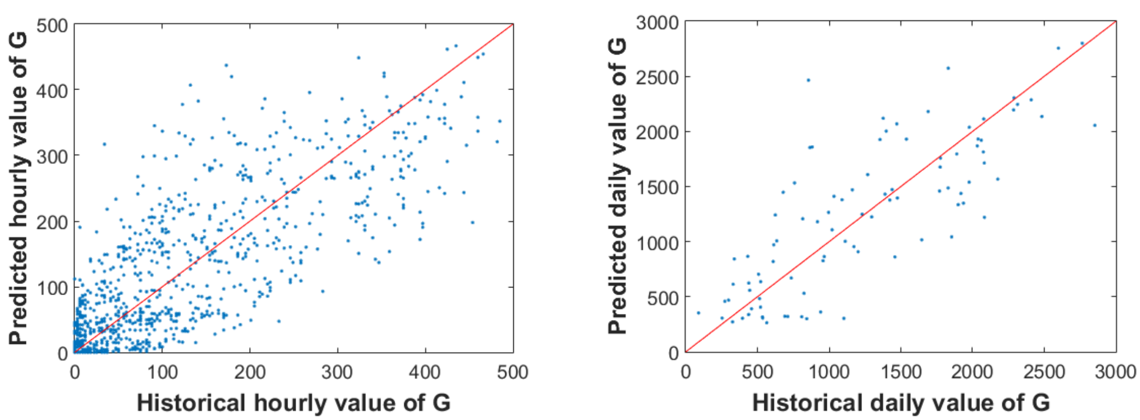


Figure 4.5: Predicted solar prediction as function of the historical horizontal solar prediction G (in W/m^2) with models created with data from April to October. **Left**: hourly – **Right**: daily

Figure 4.5 shows that predicted values underestimate high values of solar radiation and overestimate low values of solar radiation. With regard to the global accuracy, coefficients of determination are 0.75 and 0.63, respectively for the hourly and daily data. These values may be considered as acceptable for solar radiation considering its high uncertainty. However, the solar prediction model has been created based on 127 days mainly during summer, while it has been tested for the winter period. Therefore, accuracy may be improved with a larger set of data and with more winter data.

To verify this assumption, a new version of the solar prediction model is developed by adding data from November 1st 2016 to December 31st 2016 to the training stage. The tested period is from January 1st 2017 to March 31st 2017. This model will not be used for the rest of the modeling since data cannot be used at the same time to create the solar prediction model and to test the performance of the proposed predictive controller not to skew the results. The aim of this new model was to study the potential of a solar prediction model with a larger set of data.

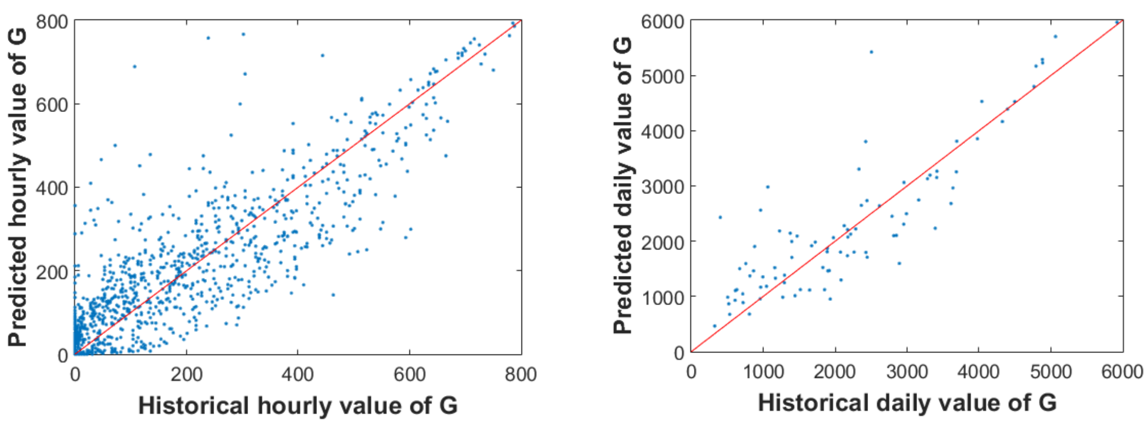


Figure 4.6: Predicted solar prediction as function of the historical horizontal solar prediction G (in W/m^2) with models created with data from April to December. **Left**: hourly – **Right**: daily

Comparing **Figure 4.5** and **Figure 4.6** shows the spectrum of tested hourly and daily values was expanded and the data dispersion was decreased with the increase of the data set. Moreover, the increase of calculated coefficients of determination corroborate this observation (0.82 and 0.74, respectively for the hourly and daily data). Therefore, increasing the size of data set improved the accuracy of the developed solar prediction model.

4.2.2. TASK B.3: PARAMETRIC STUDIES ON THE SELF-LEARNING CONTROLLER

To have a better understanding of the behavior of the developed simplified self-learning controller and to be able to choose the best value, some parametric studies on algorithm parameters and weather prediction model parameters are presented. Parametric study on algorithm parameters are presented for the house without basement only. Concerning the parametric study on weather prediction model parameters, results on both houses with and without basement are presented to study the difference of the weather forecast uncertainties on both houses.

4.2.2.1. Algorithm Parameters

Figure 4.7 shows the thermal comfort based on the predicted percentage of dissatisfied people (PPD) with the following parameters: 1 clo – 1.1 met – 0.1 m/s. To represent it, the time per day with a PPD > 10% (hr/day) is chosen, which represents the time per day with thermal comfort issues. Chosen values for the reference case are:

Prediction method = Max $\quad Tmax_{learning\ process} = 24 \quad Tmin_{learning\ process} = 21$

$Tmax_{low-level} = 23 \quad Tmin_{low-level} = 21$ $\quad$ IC = 5 $\quad$ BRL = 1

It is apparent that in most of cases (except $Tmax_{learning\ process}$), values of these parameters highly influence the performance of the controller. Results of parameters may be divided in two parts. For some of them, a clear conclusion may be drawn: taking the maximal for the prediction method and choosing 22°C for $Tmin_{learning\ process}$ allows a significant decrease of the peak consumption, mid-peak consumption and thermal discomfort. Moreover, it appears that having $Tmin_{low-level}$ higher than 21°C increases considerably the consumption during peak periods. However, for the other parameters, the choice is sometimes less evident with contradictory effects. Moreover, most of these parameters are dependent on each other's. Therefore, the best combination of values cannot be selected only by chosen the best result for each parametric study.

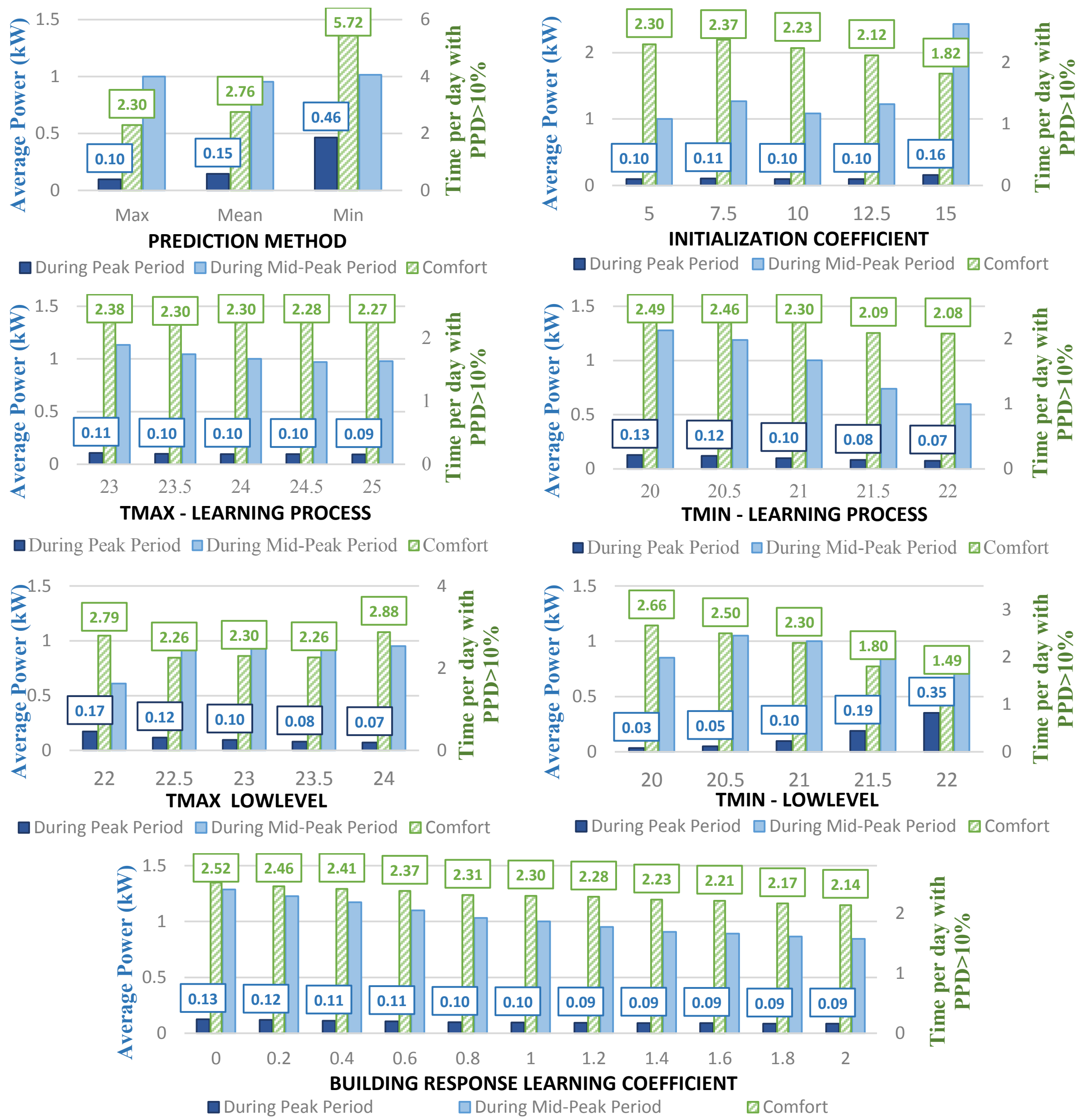


Figure 4.7: Results of parametric studies on controller parameters based on the reference case.

Therefore, in order to have a better image of the influence of these parameters on the controller performance, **Figure 4.8** presents 3 controller performances (thermal discomfort, peak consumption and mid-peak consumption) for different values of 3 parameters: $Tmax_{low-level}$, the BRL coefficient and the initialization coefficient. Other parameters are constant, with values chosen based on previous parametric studies:

Prediction method: Max $\quad Tmax_{learning\ process} = 25°C$

$Tmin_{low-level} = 21°C \quad Tmin_{learning\ process} = 22°C$

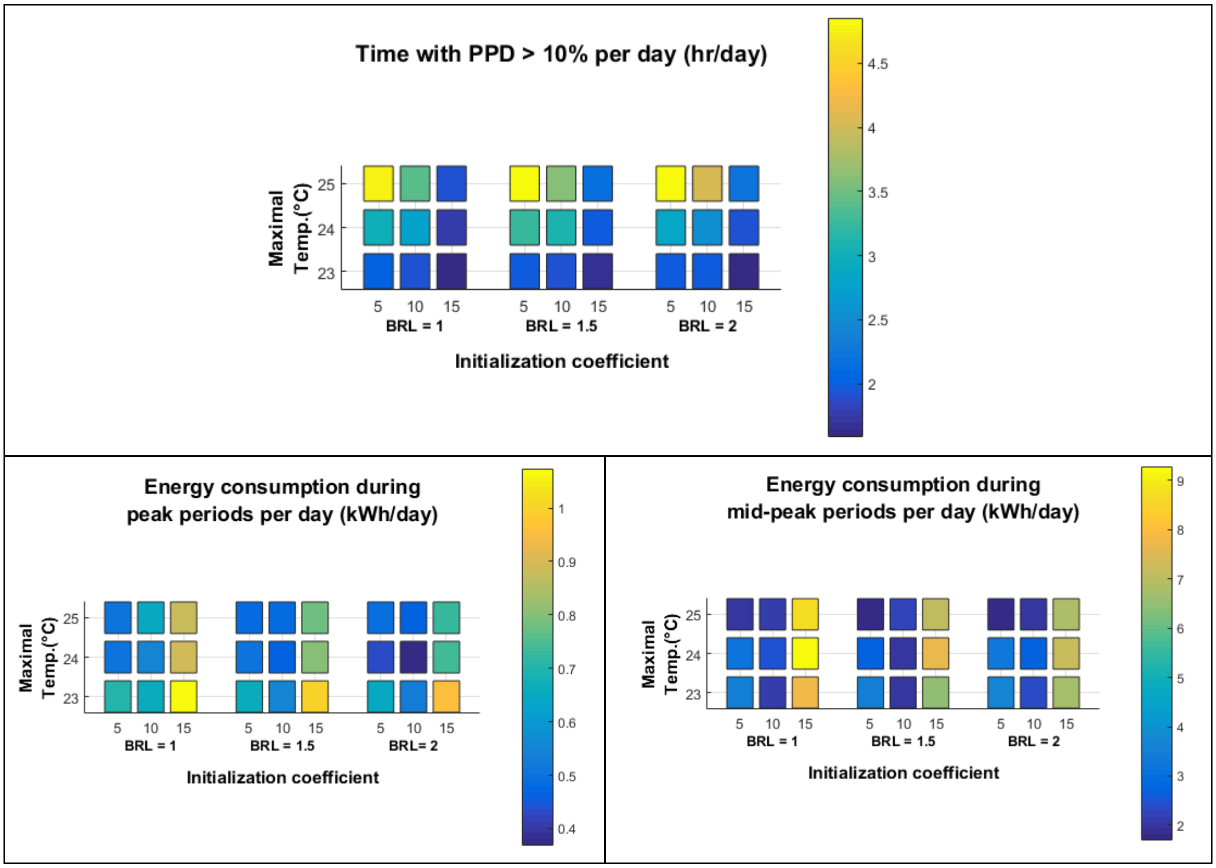


Figure 4.8: Thermal comfort, peak consumption and mid-peak consumption as function of $Tmax_{low-level}$, the building response learning coefficient and the initialization coefficient

Figure 4.8 shows that decreasing the peak energy consumption and improving the thermal comfort have contradictory objectives. Also, some values may be excluded, such as IC=15, which reaches a high consumption during peak and mid-peak periods. To select the best values combination, some are extracted based on the results presented in **Figure 4.8**. Combinations consumption during peak and mid-peak periods is presented as function of the thermal discomfort in **Figure 4.9**. **Figure 4.9** reveals a better performance for achieving the 3 objectives (decrease the thermal discomfort, peak and mid-peak energy consumption) for one combination: $BRL = 1.5$, $IC = 10$ and $Tmax_{low-level} = 23°C$. Finally, the selected combination is:

Prediction method = Max $\quad Tmax_{learning\ process} = 25 \quad Tmin_{learning\ process} = 22$

$Tmax_{low-level} = 23 \quad Tmin_{low-level} = 21 \quad$ IC = 10 $\quad$ BRL = 1.5

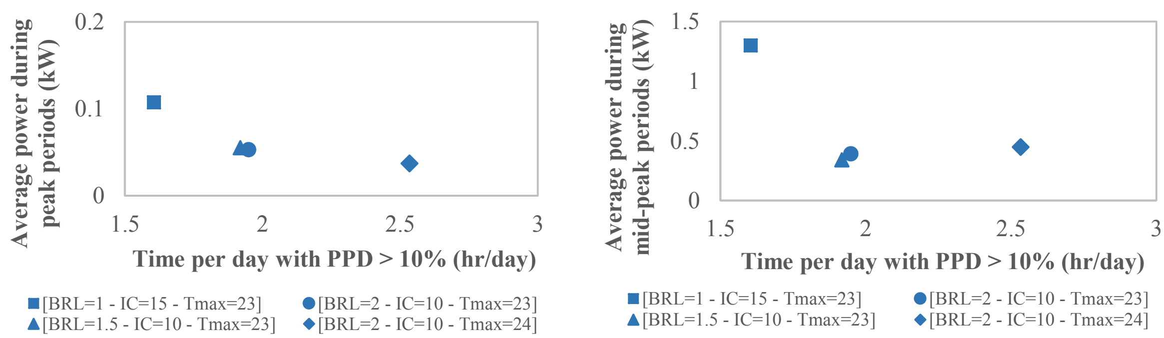


Figure 4.9: Average power during peak periods (left) and during mid-peak periods (right) as a function of the thermal discomfort for the selected combinations.

These values will be used in the rest of the study for the both houses (with and without basement). To better understand what an IC of 10 signifies, the resulting initialization matrix is presented in **Table 4.7** using 14 ambient temperature categories (i.e. reference case).

Table 4.7: Used powers for the initialization matrix for the reference case

Ambient temp. category	1	2	3	4	5	6	7	8	9	10	11	12	13-14
$P^i(T)$ [W/m²]	120	110	100	90	80	70	60	50	40	30	20	10	0

4.2.2.2. Influence of the Weather Category Number

As paragraph 3.3.1.3 shows, the solar prediction model translates hourly values of ambient temperatures and solar radiation into a defined number of half-daily temperature and solar categories, the only information about the weather forecast considered by the controller. Therefore, the number of considered categories influences forecast accuracy, and possibly controller performance as well. In the following section, the influence of the solar and temperature category numbers was studied in both case studies. The reference case uses 3 solar categories and 14 temperature categories as inputs. All studies proceeded from November 1 2016 to January 31 2017.

Influence of the Solar Category Number

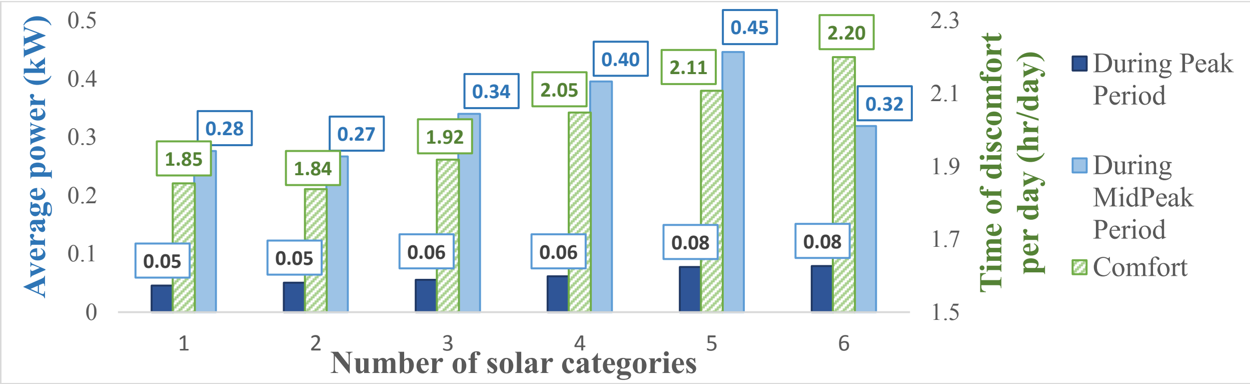


Figure 4.10: Controller performance as function of the solar category number (without basement)

Figure 4.10 shows the average injected power during peak periods, mid-peak periods and the time of discomfort per day for the house without basement as a function of the solar category number. It shows that only increasing the number of solar categories from 1 to 2 slightly improves the performance of the controller. It can be concluded that increasing the solar category number to a higher value than 2 decreases the performance of the controller at peak consumption, mid-peak consumption, or thermal comfort.

This may occur because increasing the number of solar categories makes it harder for the controller to learn from the historical responses of the building. Indeed, the amount of historical data per categories decreases with increasing the category number, making it more difficult for the learning process to predict the amount of energy required. Moreover, with the increase of the solar category number, the update process of the initialization matrix becomes less efficient. Historical energy consumption during a day with a weather forecast $[T^i; S^i]$ is used to update categories $[X; S^i]$ and $[T^i; X]$ (i.e. with a constant temperature category or a constant solar category). Therefore, as the number of solar categories increases, the controller takes more time to update the initial energy consumptions, leading to an increase of the thermal discomfort.

The tendency is different for the house with basement (see **Figure 4.11**). Considering only one solar category (i.e. excluding solar radiation in the prediction process), the mid-peak energy consumption is particularly high. For solar categories of 2 to 6, variations in peak consumption, mid-peak consumption and thermal discomfort are not significant. The basement being insufficiently influenced by solar radiation compared to the previous house might explain this difference. Therefore, for both house types, a solar category number equal to 2 seems to lead to relevant controller performance.

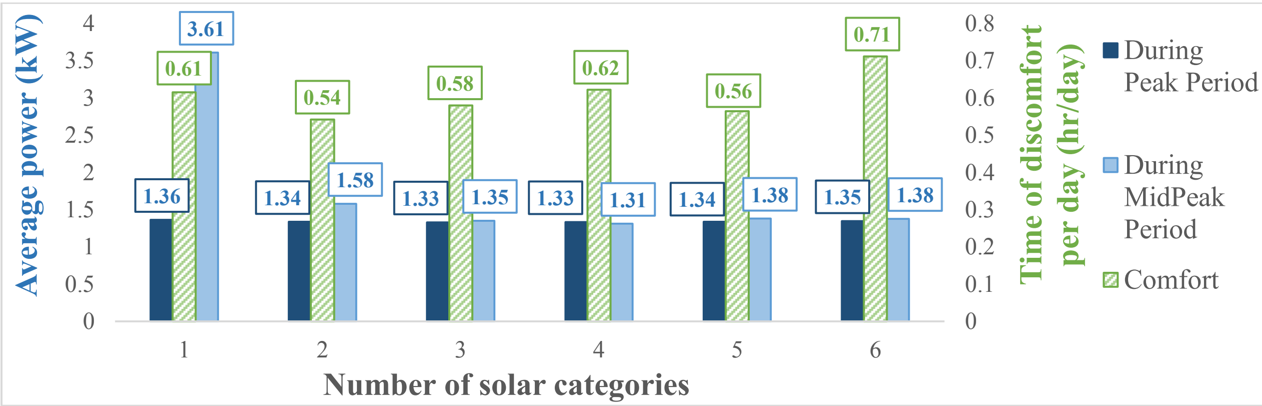


Figure 4.11: Controller performance as function of the solar category number (with basement)

Influence of the Temperature Category Number

The number of temperature categories defines the range of minimal ambient temperature for each category using -40°C as the minimal ambient temperature and 30 °C as the maximal ambient temperature. For instance, having 7 weather categories means that each temperature category uses a $\frac{30-(-40)}{7} = 10$ °C minimal ambient temperature range. Therefore, increasing the number of temperature categories decreases the considered temperature range for each category.

In the control algorithm, energy consumption values of the initialization matrix were defined based on 14 categories. Modifying the number of temperature categories modifies the initialized values, which could affect the controller's performance. Therefore, to study only the effect of the temperature category number, powers presented in **Table 4.7** were adapted:

- When the temperature category number increases, initialized powers are built on previous data for the same ambient temperature range. Let us give an example: the initialized power for [-25; -20]°C was set at 90 W/m^2 for the reference case. If the number of temperature category doubles, power for [-25; -22.5] °C and [-22.5; -20] °C are set at 90 W/m^2.
- When the temperature category number decreases, initialized powers are built on average powers defined for the reference case. Therefore, taking the same example, if the temperature category number is divided by two, power for [-30 ; -20] °C is the average of initialized powers of [-30 ; -25]°C and [-25 ; -20]°C of the reference case (i.e. 95 W/m^2).

Figure 4.12 (without basement) shows the controller's performance improves when the number of temperature category rises from 1 to 14 (i.e. from no consideration of ambient temperature in the prediction process to the consideration of ranges of 5°C) for the house without basement. Without a basement, ambient temperature has a great influence on the energy demand. If the controller performance between 14 and 20 temperature categories can be considered as constant, the controller's performance with 35 temperature categories (i.e. with temperature ranges of 2°C) decreases. In the same way as solar radiation categories, increasing the number of temperature categories may decrease the amount of data for each category and also therefore the efficiency of the update of the initialization matrix. Consequently, the controller's decline in performance as a result of data decrease cannot be compensated by increasing the controller's accuracy anymore.

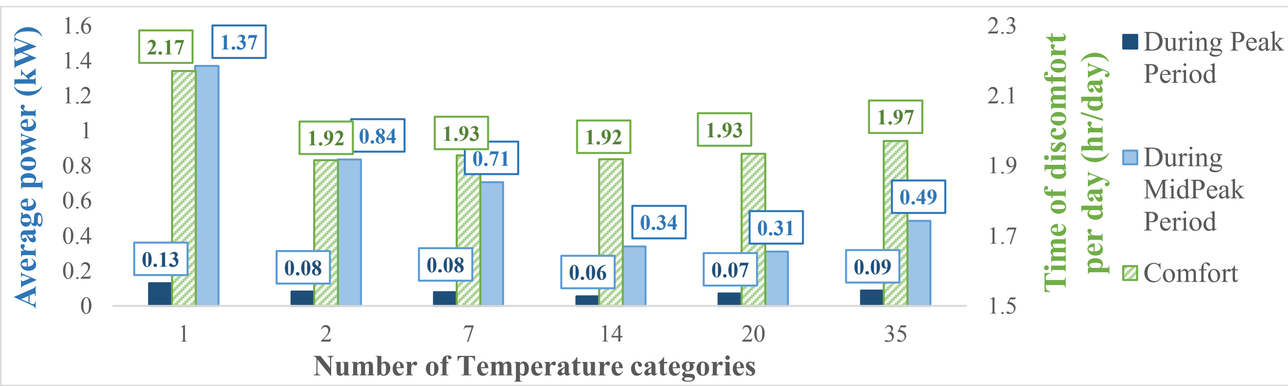


Figure 4.12: Controller performance as function of the temperature category number (without basement)

The results tendency is different for the house with basement (see **Figure 4.13)**. The same stabilization as for the solar category number appears from 7 to 35 categories given the lower effect of ambient temperature on basement energy consumption. However, these results show a significant decrease in controller performance between 1 and 2 temperature categories, possibly due to the average powers used in the initialization matrix. Indeed, one temperature category means that regardless of solar and temperature predictions the controller begins with a power of 55.7 W/m^2 (average power of the 14 temperature categories in **Table 4.7**). However, with two temperature categories (i.e. [-40; -5]°C and]-5 ; 30]°C), initial powers of these two categories were the average powers of the seven first and last categories of **Table 4.7** (i.e. 90 W/m^2 and 21.4 W/m^2). Therefore, considering the tested period has great ambient temperature variations (from November 1st to January 31st), the system probably had insufficient days to learn correctly, especially for minimal ambient temperatures greater than -5°C that started with low night powers

(21.4 W/m^2). As the controller is built, if temperature is too low in the evening, consumption during mid-peak period will increase first, explaining perhaps the significant increase of mid-peak consumption.

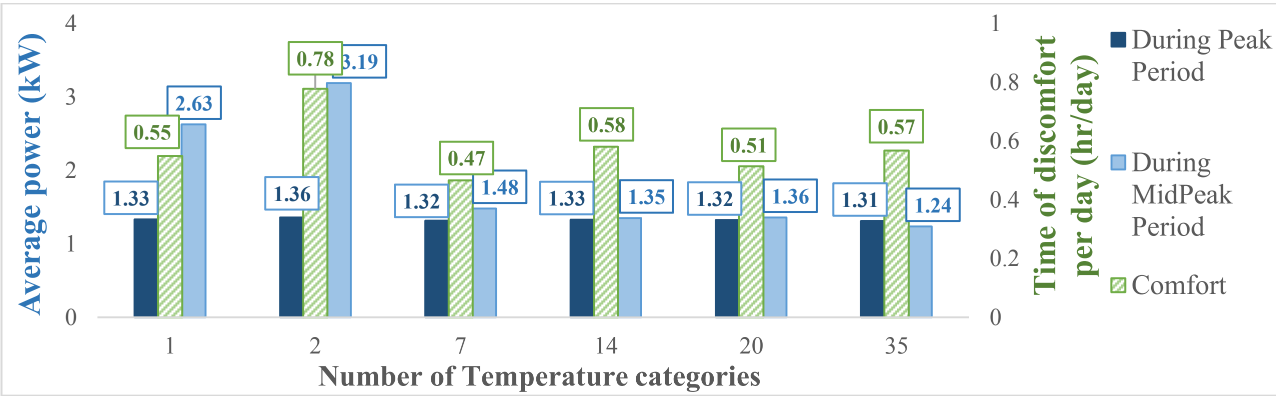


Figure 4.13: Controller performance as function of the temperature category number (with basement)

Therefore, for the rest of the research, 14 temperature categories and 2 solar categories are used in for the house without basement, and 7 temperature categories and 2 solar categories for the one with basement.

4.2.3. Task B.4: Results depending on the Control Strategy

4.2.3.1. Energy Consumption and Thermal Comfort Analysis

Simulations were performed for a longer period (November 1st 2016 to March 31st 2017) in taking into consideration previous conclusions on the number of solar and temperature categories. Other proposed control strategies (C1, peak-shifting control strategy and night-running control strategy) were studied during the same period to compare their performance.

Building without Basement

Figure 4.14 compares the performance of four controllers in terms of peak average supplied power, mid-peak average supplied power and thermal discomfort for the house without basement. This figure shows that compared to control C1, the other three controllers achieve the goal of peak-shifting with a great decrease in average power during peak period (at least 96%), during mid-peak period (at least 77%) and in the amount of time of thermal comfort issues in a day (at least 26%).

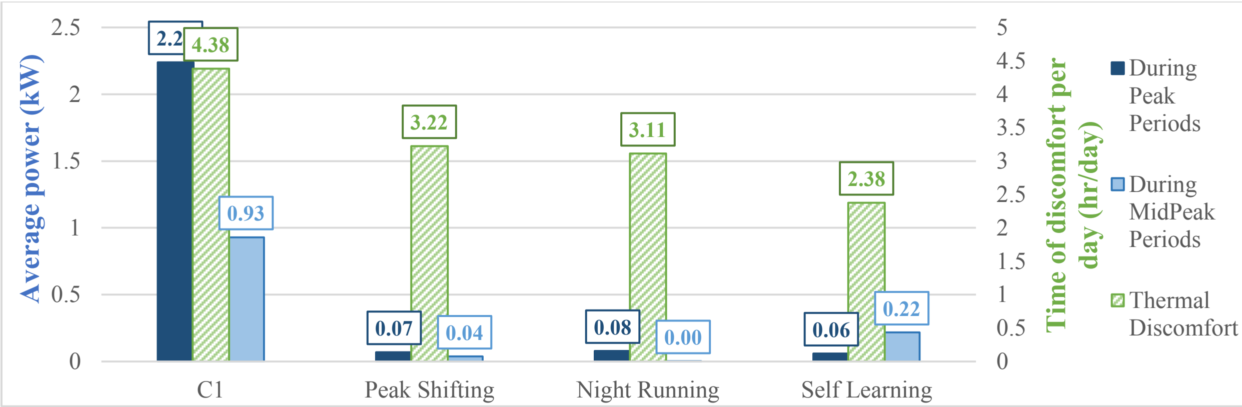


Figure 4.14: Comparison of the 4 controllers in terms of peak energy consumption, mid-peak energy consumption and thermal discomfort

Moreover, compared to the two other controllers that exceed 3hrs of daily thermal discomfort, the self-learning controller scores a higher performance, with a 2.38hrs per day. However, the average power supplied during mid-peak period is higher for the self-learning controller, which decreased the supplied power by 77% at mid-peak hours compared to almost 100% in the two others.

To understand the differences in thermal comfort and in mid-peak consumptions, ranges of PMV observed during the complete simulation are plotted in Figure 4.15 for the control C1, the peak-shifting control strategy and the self-learning predictive controller. The night-running control strategy is not represented since results are very close to the peak-shifting control strategy. These plots represent, the hourly mean value, interquartile range, minimal and maximal value, and outliers. Values are considered as outliers if they are higher than $1.5(q_3 - q_1)$ or lower than $-1.5(q_3 - q_1)$ with q_3 the 75$^{\text{th}}$ percentile and q_1 the 25$^{\text{th}}$ percentile.

Previous results showed a high value of daily thermal discomfort with the conventional controller C1, which may be surprising. PMV results (see **Figure 4.15**) show the thermal discomfort with controller C1 is due mainly to under-heating. In fact, the original building's temperature set-point of 21°C was maintained for controller C1. However, these results show that, considering the cold wall and window temperatures during winter, a temperature set-point of 21°C is slightly too low to ensure a good thermal comfort in the house.

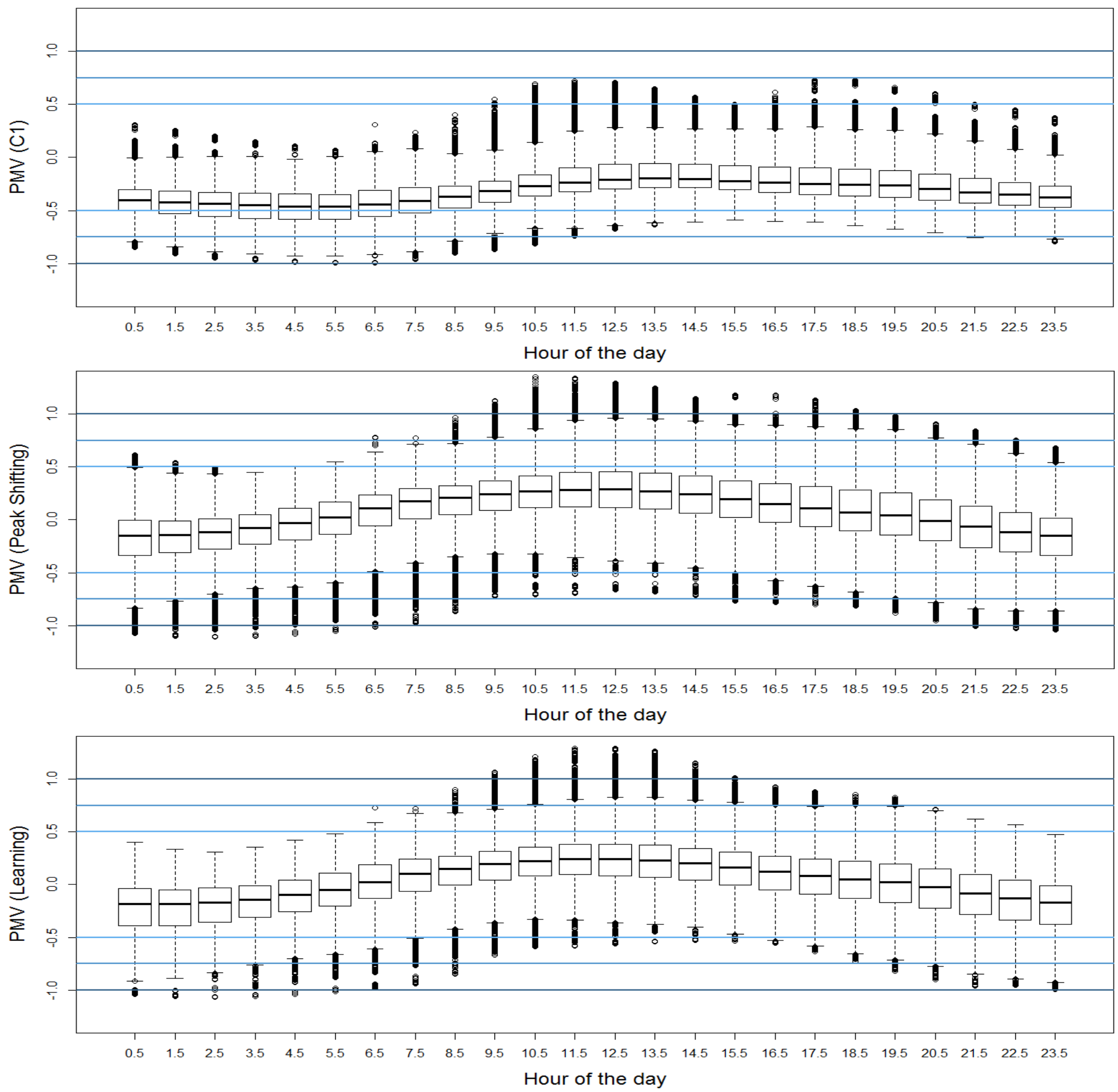


Figure 4.15: Comparison of the hourly PMV for the controller C1 (**top**), the peak-shifting control strategy (**middle**) and the self-learning control strategy (**bottom**) for the house without basement

Comparing PMV for the peak-shifting control strategy and the self-learning controller strategies, one can conclude that:

- During the afternoon, the evening and the night, maximal values of PMV for the peak-shifting control strategy are close to 1 while maximal values of PMV for the self-learning controller are closer from 0.75.

- During the day, interquartile ranges of PMV for the self-learning controller are smaller than ranges of PMV for the peak-shifting control strategy.

Therefore, over-heating and under-heating have been decreased using the self-learning controller compared to the peak-shifting strategy. These results confirm the decrease in daily thermal discomfort previously displayed. Moreover, observing the average off-peak and mid-peak powers for both controllers, it can be concluded that the decrease of over-heating is due to a small shift in consumption (around 0.2 kW) from the off-peak period to the mid-peak period with the self-learning controller.

Building with Basement

Figure 4.16 shows differences in controller performance for the house with basement. The trend is overall the same as for the house without basement. Large decreases of average power during peak period (by 57%), during mid-peak period (at least by 38%) and of the thermal discomfort (at least by 67%) are also found in the house with basement. Moreover, the self-learning controller's specificity compared to the peak-shifting and night-running controllers can also be seen in its superior performance in thermal discomfort (decrease by 83% instead of 67%). However, the improvement of the thermal comfort is due to a shift in energy consumption from the night to the afternoon, leading to an increase in mid-peak average power (decrease by 38% for the self-learning controller compared to C1 instead of a decrease by 60% for the two others controllers).

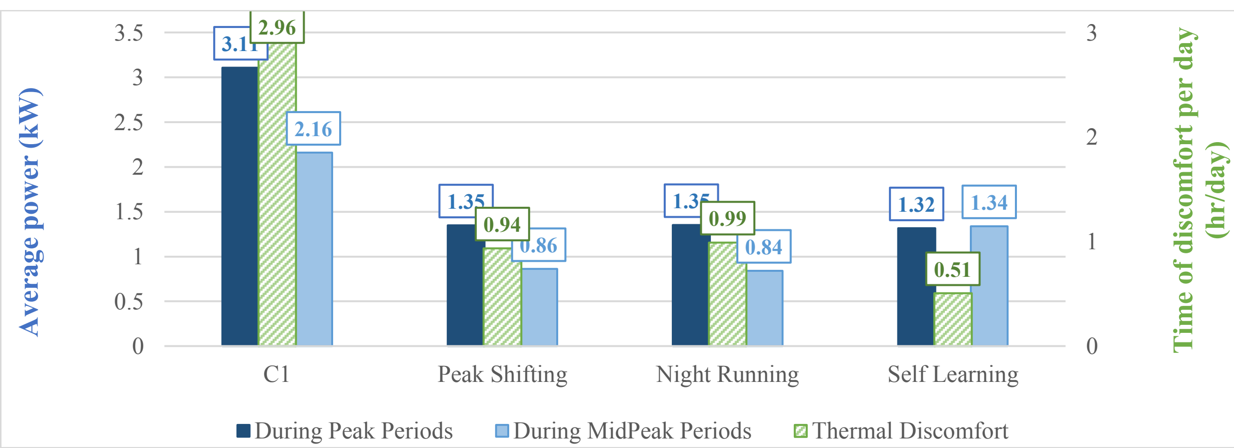


Figure 4.16: Comparison of the 4 controllers in terms of peak energy consumption, mid-peak energy consumption and thermal discomfort (with T=7 and S=2)

Similar to the house without basement, PMV ranges observed during the whole simulation are plotted in Figure 4.17 for control C1, the peak-shifting control strategy, and the self-learning predictive controller.

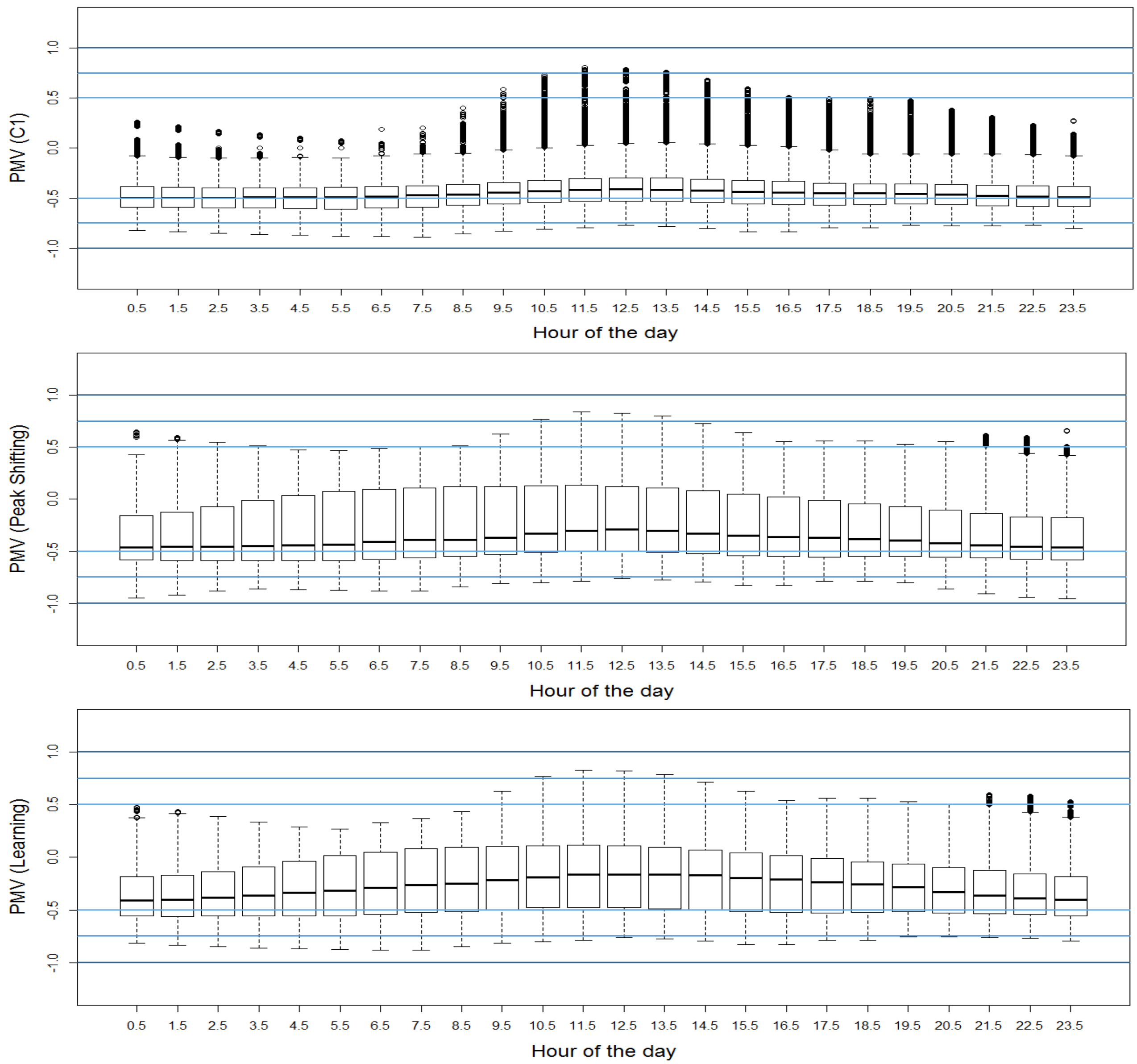


Figure 4.17: Comparison of the hourly PMV for the controller C1 (**top**), the peak-shifting control strategy (**middle**) and the self-learning control strategy (**bottom**) for the house with basement

After comparing PMV for the peak-shifting control strategy and the self-learning controller strategies, the following conclusions may be drawn:

- In the evening and at night, minimal temperatures are higher with the self-learning controller than with the peak-shifting controller.
- At night, maximal temperatures are lower with the self-learning controller than with the peak-shifting controller.
- During the day, interquartile ranges of PMV for the self-learning controller are smaller than those for the peak-shifting control strategy, and the mean is more centered in the interquartile range.

Therefore, as for the house without basement, these observations indicate a decrease in over-heating and under-heating compared to the peak-shifting strategy due to self-learning. This could explain the decrease in thermal discomfort shown previously.

4.2.3.2. Financial Analysis

The shift in consumption is environmentally significant, but financially too, for both supplier and building owner.

From an Owner's Point of View

The weekly cost for the owner with each studied control strategy is compared in Table 4.8 for the house without basement and Table 4.9 for the house with basement. These tables indicate that the 3 controllers with a shift the consumption are able to reduce the electricity bill by approximately10% for both house types and for the considered period (from November 1st to March 31st) even though the daily total energy consumption is higher. The self-learning predictive controller provides similar savings to the 2 non-predictive controllers despite a higher mid-peak consumption mainly due to a slight decrease in total energy consumption. Therefore, the developed self-learning predictive controller and the two other controllers developed with a peak-shifting aim enable significant financial savings for the owner, even if the temperature set-point is too low to maintain a good thermal comfort with controller C1.

Table 4.8: Financial savings for the house without basement

	C1	Peak-Shifting	Night Running	Learning
Total energy consumption (kWh/day)	57.79	68.74	68.67	68.23
Daily cost ($CAD/day) during weekdays	7.36	6.06	6.05	6.05
Daily cost ($CAD/day) during weekend	5.03	5.98	5.97	5.94
Weekly cost ($CAD/week)	46.87	42.24	42.19	42.12
Difference in weekly cost compared to C1		9.9%	10.0%	10.1%

Table 4.9: Financial savings for the house with basement

	C1	Peak-Shifting	Night Running	Learning
Total energy consumption (kWh/day)	77.47	82.70	82.65	80.85
Daily cost ($CAD/day) during weekdays	10.22	8.68	8.68	8.74
Daily cost ($CAD/day) during weekend	6.74	7.19	7.19	7.03
Weekly cost ($CAD/week)	64.56	57.80	57.76	57.78
Difference in weekly cost compared to C1		10.5%	10.5%	10.5%

From a Supplier's Point of View

Days extracted are: December 16th 2016 (-19.0°C); December 19th 2016 (-16.4°C); January 8th 2017 (-15.9°C) and March 11th 2017 (-17.7°C). The average power during peak period and the avoided cost are presented in **Table 4.10** for the house without basement and in **Table 4.11** for the house with basement.

Table 4.10: Financial savings for the house without basement

	C1	Peak-Shifting	Night-Running	Self-Learning
Average power during the peak period (kW)	3.47	0.23	0.26	0.49
Avoided cost for the supplier ($CAD/year/house)	-	350	347	322

Table 4.11: Financial savings for the house with basement

	C1	Peak-Shifting	Night-Running	Self-Learning
Average power during the peak period (kW)	4.98	2.61	2.62	2.56
Avoided cost for the supplier ($CAD/year/house)	-	257	256	262

These tables show that the average power during peak period is similar for the 3 developed controllers for load management. Therefore, the avoided cost for the supplier is similar: around $340 (CAD) for a house without basement and $260 (CAD) for one with basement.

Considering that there are 1.6 millions of detached houses in Québec (Statistics Canada 2017), potential savings for the supplier are considerable.

4.3. SUMMARY

In this chapter, the results of EHF modeling in TRNSYS and of the development of the simplified self-learning predictive control were presented. Studies on the potential of an EHF for peak-shifting proved that the assembly currently used is suitable for load management. At the same time, it was noted that using non-predictive controllers leads to thermal comfort issues due to some under or over-heating. The necessity of using weather predictions in the control process was thus proven.

To keep a low implementation cost, a clearness index table was developed for Montréal to predict solar radiation, using only free information available. Accuracy tests on the solar prediction model presented in this chapter proved that the solar prediction model is a suitable solution for the predictive self-learning controller.

Finally, the developed self-learning predictive controller and the other proposed non-predictive controllers were implemented in both houses. For controllers' performance presented in this chapter, see **Table 4.12** for the house without basement and **Table 4.13** for that with basement. The three controllers enable a significant decrease in thermal discomfort, average powers during peak and mid-peak periods, and allow financial savings for both supplier and customer considering a Time-of-Use tariff compared to controller C1. If the mid-peak average power is slightly higher for the self-learning controller than for the peak-shifting and night-running controllers, the thermal comfort improves, which may increase occupants' acceptance. Therefore, the developed self-learning controller seems promising for a large-scale application in residential houses.

Table 4.12: Controllers' performance compared to C1 for the house without basement (a decrease relative to C1 is shown with a negative sign)

Controller	Thermal Discomfort	Average Mid-Peak Power	Average Peak Power	Cost for the customer	Cost for the supplier ($CAD/year)
Peak-Shifting	- 26.5%	- 96.0%	- 96.9%	- 9.9%	- 350
Night Running	- 29.0%	- 99.8%	- 96.5%	- 10.0%	- 347
Self-Learning	- 45.8%	- 76.7%	- 97.3%	- 10.1%	- 322

Table 4.13: Controllers' performance compared to C1 for the house without basement (a decrease relative to C1 is shown with a negative sign)

Controller	Thermal Discomfort	Average Mid-Peak Power	Average Peak Power	Cost for the customer	Cost for the supplier ($CAD/year)
Peak-Shifting	- 68.4%	- 60.1%	- 56.6%	- 10.5%	- 257
Night Running	- 66.5%	- 61.0%	- 56.5%	- 10.5%	- 256
Self-Learning	- 82.9%	- 38.0%	- 57.7%	- 10.4%	- 262

CONCLUSION

5.1. SUMMARY AND CONCLUSION

The objective of this research is to study the ability of an EHF to shift the electrical consumption from peak to off-peak periods. Achieving this goal was challenging for three reasons—first, the solution should maintain an acceptable thermal comfort for the occupants; second, the solution should provide a good performance in terms of peak shifting and thermal comfort for all residential houses (i.e. with and without basement); third, the implementation cost of the solution should be as low as possible in order to have a potential large-scale implementation.

To decrease the energy consumption during the peak period with a low implementation cost, this study focused on controlling the EHF. The literature review on BITES control for load management highlighted some thermal comfort issues with the use of intermittent non-predictive control strategies with active BITES. However, most of the time studies testing a night-running strategy with active BITES used PCM in their assembly. Therefore, a study on an assembly with a concrete-only storage system was required.

Therefore, an alternative modeling in TRNSYS was proposed to model the EHF within the floor assembly. The proposed solution consists in creating a fictitious zone to insert a surface heat flux inside the floor assembly. A parametric study on layers' thickness proved that the assembly used presently in Québec was suitable for load management. Finally, a study on the thermal comfort in a house with a night-running strategy showed that rooms were sometimes overheated and sometimes underheated, with high variations depending on the room.

Therefore, the first step of this research has verified the assumption proposed by the author after the literature review: a predictive control is required for maintaining a good thermal comfort while decreasing the heating energy consumption significantly during peak periods.

As shown in the literature review, MPC is the most used supervisory predictive control at the moment. MPC proved to have a high performance in terms of thermal comfort or energy consumption. However, the results of some studies should be adjusted since most of them are simulations based, without consideration of all/some uncertainties (weather, occupancy and model uncertainties). Finally, and most importantly for this study, MPC still has to overcome some challenges. Indeed, even if some MPC formulations have been developed to decrease the computation time or to increase the robustness of the controller to uncertainties, MPC still needs a building model. If increasing the use of Building Information Modeling (BIM) may be a solution for large buildings, these MPC formulations may not be the solution for this research. Considering a widespread residential application, the creation of a building model and the implementation of an optimization process, as simple as they may be, will remain expensive. Therefore, using MPC is not an optimal solution for this application.

Otherwise, predictive model-free controllers, simple and cheap to implement, may have a higher performance than conventional controllers without adding too much complexity. Moreover, their intuitiveness may influence the occupant to accept the controller. However, thermal comfort is not always achieved in reviewed studies. Moreover, their application has not been tested on real buildings. Consequently, predictive model-free controllers seemed a particularly interesting approach for reaching the objectives of this research.

Therefore, a simplified self-learning predictive control was developed, while also ensuring a significant shift in consumption and an acceptable occupants' thermal comfort with a low implementation cost. The objective was to develop a controller able to start without any information of the building, ensuring a significant shift of the consumption from peak to off-peak periods while ensuring a good thermal comfort.

As shown in the literature review, many studies do not consider weather uncertainties impacting the controller's performance. Therefore, the self-learning controller comprises its own solar prediction model, allowing it to use weather conditions forecast available online and consider the real weather's uncertainty. Accuracy tests on the solar prediction model show a good performance of the model. Moreover, using a clearness index table helped create a tool usable for other solar prediction applications.

The simplified self-learning controller is based on the consideration of previously applied consumption and the corresponding response of the building. In this way, the self-learning controller refines its prediction and the scheduling of the consumption to ensure a good thermal comfort while cutting the consumption during peak and mid-peak periods.

To compare its performance, three other controllers have been proposed: control C1, considering a stable indoor temperature during all day; control C2 – night-running control strategy, heating at a high power during the night and heating during the day only if the indoor temperature drops below 20°C; and control C2 – peak-shifting strategy, heating at a high power during the night and during the mid-peak period if the indoor temperature drops below 21.5°C.

Results of the proposed controllers showed that the three controllers for peak shifting (night-running control, peak-shifting control and self-learning predictive control) enable a significant decrease in thermal discomfort and average powers during peak and mid-peak periods. The controllers also allow financial savings for the supplier and for the owner by using a Time-of-Use tariff compared to controller C1. If the mid-peak average power is slightly higher for the self-learning controller than for the peak-shifting and night-running controllers, the thermal comfort improves and may increase the occupants' acceptance. Therefore, the developed self-learning controller seems promising for a large-scale application in residential houses.

Novelties of this research are summarized:

- Modeling of an EHF in TRNSYS
- Parametric study of all assembly layers' thickness of an EHF on the same assembly
- Study of a multi-zone building's thermal comfort with an EHF with a night-running control strategy
- Development of a simplified self-learning predictive controller providing a good performance in terms of peak shifting and occupants' thermal comfort even considering weather uncertainties

5.2. FUTURE WORK AND RECOMMENDATIONS

Recommended future research work on the predictive control of an EHF with an aim of peak shifting follows from the advancements and limitations of the present study:

- The proposed solar prediction model may be used for other solar applications. Therefore, its use may be extended by increasing the size of the data set for the training stage or by increasing the number of categories to improve accuracy.
- The proposed simplified self-learning controller should be implemented in other building models to test its adaptability to other buildings.

- Experimental studies are required in order to confirm the potential of the self-learning controller in terms of peak shaving and occupants' thermal comfort.
- More studies may be conducted to improve the self-learning algorithm by refining its prediction method or the consideration of weather forecast information.
- Since many houses in Québec have a basement, the controller may also integrate the possibility to control a mechanical ventilation system to send the heat from the basement to the ground floor.

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