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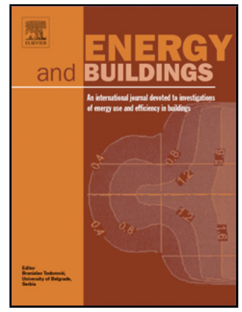

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Authors: Hélène Thieblemont, Fariborz Haghighat, Ryozo Ooka, Alain Moreau

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Predictive Control Strategies based on Weather Forecast in Buildings with Energy Storage System: A Review of the State-of-the Art

Hélène Thieblemont[1], Fariborz Haghighat[1*], Ryozo Ooka[2], Alain Moreau[3]

[1]Department of Building, Civil and Environmental Engineering,
Concordia University, Montreal, Canada, H3G 1M8
[2]Institute of Industrial Science, University of Tokyo, Tokyo, Japan
[3]Laboratoire des technologies de l'énergie d'Hydro-Québec, Shawinigan, Canada

Highlights:

- A classification of anticipatory controls is proposed.
- Anticipatory control strategies are discussed in terms of several issues.
- Achievements and limitations of Model Predictive Control (MPC) is discussed.
- New MPC formulations, developed to solve current issues of MPC, are reviewed.
- Limitations are summarized and future research directions are suggested.

Abstract

Energy storage systems play a crucial role in decreasing building energy consumption during peak periods and expanding the use of renewable energies in buildings and communities. To have a high system performance, the energy storage system has to be properly controlled while maintaining a comfortable thermal environment for the occupants. However, defining the optimal charging period for a storage system may be difficult since storage systems address issues with conflicting needs between cost saving and thermal comfort. Moreover, with the increase of the use of renewable energies, the complexity increases with the consideration of the renewable energy production. As a result, the decision process should be able to predict both loads and renewable energy production in order to increase the storage system efficiency. This necessity explains the increasing interest during the last decade for predictive control, i.e., control system considering the forecasting.

This paper reviews the recent advancements in building predictive control with energy storage system. Special attention is paid to its limitations and abilities.

Keywords: Storage; Predictive Control; Model Predictive Control; Weather Forecasting

*Fariborz.Haghighat@Concordia.ca

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Nomenclature			
BITES	Building-Integrated Thermal Energy Storage	**PPD**	Predicted Percentage of Dissatisfied
CHP	Combined Heat and Power	**RES**	Renewable Energy System
GSHP	Ground Source Heat Pump	**TABS**	Thermally Activated Building System
MPC	Model Predictive Control	**TES**	Thermal Energy Storage
PMV	Predicted Mean Vote	**WCC**	Weather Compensated Control

Definitions	
Predictive Control	Supervisory control taking weather predictions into consideration
Building model	Model of the building (including the storage system model)
Thermal violations	Violation of the acceptable indoor temperature range
Heating/cooling System	System providing heat/cool to the building or to the storage system

Control stages of an integrated system with storage

ASHRAE (2003) and Dorgan et al. (2001) determined different control stages for storage system.

Operating Strategy	Main goal of the controller. For building with storage, operating strategies may be: Demand shaving - Demand shifting – Energy consumption minimizing – Energy cost minimizing - Maximal use of renewable energies etc.
Operating Mode	Combination of actions undertaken at a specific time by the controller in order to achieve the operating strategy. For building with storage, operating modes may be: charging the storage, discharging the storage, direct heating from the heating system, discharging the storage + direct heating, etc.
Control Strategy	Name given to a specific sequence of operating modes over the storage cycle (usually diurnal). A simple example may be a night-running control strategy: considering a day/night tariff, this control strategy will apply a charging operating mode during all night (when electricity is cheap) and a discharge-operating mode during the day. For predictive control, the control strategy varies each cycle as a function of the forecast.
Supervisory Control Strategy	Process that determines the control strategy considering the operating strategy.

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Introduction

Electric and thermal energy storage systems play a crucial role in decreasing building energy consumption during peak periods and expanding the utilization of renewable energies in buildings (Najafian et al., 2015; Olsthoorn et al., 2016). The energy storage system has to be properly controlled while maintaining a satisfactory occupants' thermal comfort to improve system performance. Consequently, storage systems' control has been widely studied as reviewed by Yu et al. (2015). However, defining the optimal charging period for a storage system may be difficult since storage systems address issues with conflicting needs. On one hand, to take advantage of time-of-use tariffs, a high amount of energy should be stored during off-peak periods. On the other hand, the stored amount of energy should not be higher than the loads for avoiding energy losses or thermal comfort issues in the case of building-integrated with thermal energy storage (BITES) (Bastani et al., 2015; Thieblemont et al., 2016).

Moreover, with the increasing rate for utilization of renewable energies, the complexity of the problem increases with the consideration of renewable energy production. As an example, if a storage system is always charged during off-peak periods, energy loss may appear if demands are low and the storage system is full. As a result, a decision process should be able to predict both supply and demand to increase the storage system efficiency. This process is called "Predictive control".

So far, most of the reviews on control of storage system are limited to specific applications: Sun et al. (2013) reviewed controls of storage system applied to peak load shifting; Zamora & Srivastava (2010) reviewed controls of storage system in micro-grids; Pintaldi et al. (2015) reviewed controls of storage applied to solar cooling applications. A complete review of control of storage systems was realized by Yu et al. (2015) but predictive control has not been widely addressed. Therefore, to shed more light on the recent achievements of predictive controls of storage systems, this paper aims to review the current state-of-the-art. This review only considers studies based on a building with a storage system controlled based on the weather forecast. Studies focusing on buildings that do not consider specifically its thermal mass as a storage medium will not be considered in this study. Moreover, the focus of this study is on the improvement of the storage performance due to predictive control. Therefore, comparisons in this study will be performed between system with and without predictive controller. First, various predictive control strategies are classified and reviewed, and then the limitations and abilities of predictive controls are discussed.

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1. Supervisory Predictive Control Strategies

Building systems control is often divided into three categories (Dounis & Caraiscos, 2009; Perera, Pfeiffer, & 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 suggested supervisory control strategies based on some features (weather parameters with sometimes building and/or storage parameters) for controlling the storage system, without using building model or historical data. They are defined in this study as “model-free control strategies”.

1.1. Model-free Control Strategies

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

1.1.1. Control of the Heating/Cooling System

Some model-free controllers manipulate directly the heating/cooling system variables. Cho & Zaheeruddin (2003) conducted a study with a building including a hydronic floor heating system. The authors suggested 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.

1.1.2. Control of Temperature set-point

Controlling temperature set-points is often suggested since their control at the component level is easy to implement by classical controllers. However, different approaches may be observed between studies, mainly on the selection of the parameters and the manipulated variables as shown

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in Figure 1. Considering the choice of parameters, three categories may be defined: the weather forecast only, weather forecast and building characteristics, and dynamic electricity prices.

Weather Forecast Only: Candanedo (2011) suggested to adjust the temperature set-point of a hot water tank and a building's zone air as a function of the solar radiation level for the current day and the next day. The control was based on a pre-computed table built on expectations and a model of BIPV/T system and the water tank. Therefore, this study is not completely model-free. To help the understanding of the method an example is given. During a sunny day followed by a cloudy day, the tank and solar house temperature set-points were increased to store energy for the cloudy day; in contrast, during a cloudy day followed by a sunny day, the tank and solar house temperature set-points remained at their baseline to take advantage of solar radiations on the following day. Indoor temperature was maintained using a PID controller. Results revealed the possibility for the storage tank to provide enough energy during cloudy days even in a cold climate. Still using only the weather forecast, Barzin et al. (2016) proposed a predictive control for a hut with PCM-impregnated gypsum wallboard. They suggested to control wall temperature set-point as a function of two parameters – the cloudiness of the sky and the dynamic electricity price. They defined a limit between the on-peak and off-peak electricity price, called in the study "optimal 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; in contrast, 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. The energy consumption increased by 73% compared to the other hut. Therefore, this type of predictive control may give good results in case of active storage system. Inversely, it may not be applied to BITES, for which the discharge cannot be controlled, due to the uncertainties.

Weather Forecast and Building Parameters: 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

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(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 as a function of 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 radiations (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.

Dynamic Electricity Price Predictions: 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.

As a result, model-free control strategies provide promising results and are particularly simple to implement. However, they have not been tested yet in real buildings, there is no study on peak shaving and they may cause thermal discomfort issues in the case of passive discharge storage mainly due to weather uncertainties. Nevertheless, their low cost is adapted to a large-scale application and their intuitiveness may help occupants' acceptance. Therefore, model-free control strategies should be further investigated and tested on real buildings and under real conditions (i.e. presence of occupants).

1.2. Intelligent Control

Intelligent control 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 & 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. After determining the amount of energy that had to be stored, the feed-forward controller determined the heating consumption profile during the determined off-peak

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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).

1.3. 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 & 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 may be defined, which will be called “non-optimal advanced control” in this study. These control systems use building model, but are not adapting parameters, nor apply optimization techniques.

1.3.1. Non-Optimal Advanced Predictive Control

Reynders et al. (2013) investigated a building 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 suggested predictive control. Therefore, this strategy is not advantageous.

Gwerder et al. (2008) suggested 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 radiations 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 the indoor temperature stayed within the defined comfort range most

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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.

1.3.2. Model Predictive Control (MPC)

The concept behind MPC is to optimize 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.

The main elements of a 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, & 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),

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to commercial building reported by Hilliard et al. (2015) and to HVAC systems reported by Afram & Janabi-Sharifi (2014).

Figure 3 illustrates the number of publications using MPC in a single building with a thermal energy storage system found by the author based on the publication date. This figure reveals the general interest of MPC in this area during the last decade. Therefore, the following part focuses on achievements and limitations of MPC.

2. Model Predictive Control: Main Findings and Challenges

Results of MPC applied to single building with storage systems are presented according to 4 controller performance parameters: thermal comfort, peak energy consumption, total energy consumption and applicability of the renewable energy sources in the system.

2.1. MPC Performance

2.1.1. Thermal Comfort Performance

One of the goals of the MPC application in buildings is the thermal comfort improvement (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 related 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 by various controllers in a building with floor heating system. 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. A 4.8% to 1.2% decrease in thermal discomfort issues was observed. Finally, Sturzenegger et al. (2016) studied the thermal comfort in a building with TABS controlled by MPC. A decrease by 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.

2.1.2. Peak Demand Performance

On electricity-based systems, considering peak demand reduction, MPC takes time-of-use tariff (sometimes with peak charges) 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 corresponds most of the time to the

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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 demand is reduced by preheating/pre-cooling the building at an acceptable temperature range. In the case of active storage system, peak shaving occurs by storing energy before peak periods. Most of the time, the consumption shift is not seen as an objective but as a method for decreasing the total energy cost. Therefore, only few studies presented the influence of the MPC on peak demand reduction.

Study of the peak demand reduction in using only passive BITES: When passive BITES is the only storage technique, the shift of a part of loads may be achieved by optimizing thanks to a MPC the temperature set-point. On 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 peak 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 peak demand reduction 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 peak demand from 4% to 19% depending on the building archetype was reported with the largest reductions for heavy buildings.

Study of the peak power demand reduction with active storage: Kircher & Zhang (2015) considered demand charge in the objective function of a MPC applied in a building with an ice tank. Their results showed a 25% energy consumption reduction during peak period (between 2 P.M. to 6 P.M.) and a 50% decrease of the demand charge.

Study of the peak power demand reduction with active storage and passive BITES: Oldewurtel et al. (2011) compared results using MPC with a constant electricity tariff and a time-of-use tariff in a building with a battery. They reported a 15% decrease of the peak power demand with a battery capacity higher than 1 kWh. Hajiah & Krarti (2012a, 2012b) investigated the performance of an MPC and a classical controller with fixed temperature set-points in a building with thermal mass and ice storage. Their results showed a decrease of 40

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% of the peak electrical power demand with an objective function based on demand charges only.

In summary, the use of MPC with storage system, whether they are passive or active, leads to a reduction of the peak power demand. However, effects of MPC with active BITES on peak demand have not been studied. Moreover, MPC performance in terms of peak demand reduction depends on the chosen objective function. As an example, Hajiah & Krarti (2012a, 2012b) compared results in optimizing based on the total cost or based on demand charges only in a building with thermal mass storage. Results indicated the effect of the objective function: based on the total cost, the pre-cooling started around 3 a.m to minimize the total cost; in contrast, based on demand charges, the pre-cooling started from the beginning of the night to decrease as much as possible peak demands. Moreover, different type of objective functions may be used. Ahmad et al. (2014) studied the impact of using linear or quadratic functions (mainly based on thermal comfort violations/cost and squared thermal comfort violations/costs respectively). In buildings with storage systems, the choice of the objective function depends on the operating strategy. With a quadratic function, energy usage during peak periods at a low power has a low effect on the objective function value while a high power has a great effect. Thus, a quadratic function does not help to completely shift the consumption but is interesting to level it. Conversely, in the case of load shifting, it seems preferable to use a linear function for opposing reasons. For the same reasons than for the load shaving, a quadratic function seems preferable to decrease temperature variations in order to avoid high temperature violations.

2.1.3. Total Energy Consumption Performance

Considering the total energy consumption, Table 1 summarizes energy savings as a function of storage system type. In summary, most of the studies are simulation based (sometimes with experimental chambers) thus with limited applications to real buildings. Moreover, studies considered either active BITES or active storage system but rarely both at the same time. Finally, results are highly different for energy savings (from -29 % to + 33 %) and cost savings (from 0 % to + 52 %). 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 the features that have a strong influence on the controller performance. Previous work focuses mainly on:

- The thermal mass of the building (Cigler, Gyalistras, Siroky, Tiet, & Ferkl, 2013; G. Henze & Krarti, 2005; X. Li & Malkawi, 2016)

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- The capacity of the storage system (C.-T. Li, Peng, & Sun, 2013)
- The climate and the season (Hazyuk, Ghiaus, & Penhouet, 2014; G. Henze & Krarti, 2005; Kummert, André, & Argiriou, 2006; X. Li & Malkawi, 2016).
- Time-of-use tariff considered when cost savings instead of energy savings are considered (Braun, 2003; Collazos, Maréchal, & Gähler, 2009; G. Henze & Krarti, 2005; X. Li & Malkawi, 2016; Morgan & Moncef, 2010; Oldewurtel et al., 2011)
- The desired level of thermal comfort (X. Li & Malkawi, 2016) and the proportion of occupied and non-occupied hours (Braun, 2003)
- The level of internal gains (G. P. Henze, Florita, Brandemuehl, Felsmann, & Cheng, 2010; Zakula, Armstrong, & Norford, 2015)
- The addition of appliances control or charge of electrical vehicle in the MPC (Khoury, Mbayed, Salloum, & Monmasson, 2016; Y. Zhang, Zhang, Wang, Liu, & Guo, 2015)
- The hypotheses considered for the model, the occupancy and the weather forecast uncertainties (Schirrer, Brandstetter, Leobner, Hauer, & Kozek, 2016)
- The prediction horizon (Kummert et al., 1999)

- The possibility of selling or not selling electricity to the grid in the case of renewable energies (Zhao, Lu, Yan, & Wang, 2015)

Finally, the ratio between the cost of a complex controller as MPC and its performance should be considered. Even if MPC generally has better results than other controllers, improvements may not be significant enough in some cases to justify the use of this complex controller. As an example, it seems that in most cases with only one active storage system in a building without renewable energies, MPC does not provide more savings compared to a storage-priority controller.

Table 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 storage system	(Y. Zhang et al., 2015)	TES Tank and Battery	Simulation	Solar and Wind	Considered	Day-ahead programming strategy	46 %	Cost
	(Deng et al., 2015)	Chilled water tank	Simulation	No	Not Considered	Greedy algorithm	10.8 %	Cost
							9.7 %	Energy
	(Ioli, Falsone, & Prandini, 2015)	Chilled water tank	Simulation	No	Not Considered	CL	14 %	Cost
							6%	Energy
	(Hazyuk et al., 2014)	TES Tank	Simulation	No	Not Considered	PID	-0.9 – 18.2%	Energy
						Scheduled start PID	1.7 – 23 %	
	(Beghi, Cecchinato, Rampazzo, & Simmini, 2014)	Ice Storage	Simulation	No	Considered	Constant proportion	30 %	Cost
						Chiller-priority	39 %	
						Storage-priority	0 %	
	(Ahmad, Eftekhari, Steffen, & Danjuma, 2013)	TES Tank	Simulation	Solar	Not Considered	ON/OFF as function of tank temperature	9 %	Cost
	(J. A. Candanedo, Dehkordi, & Stylianou, 2013)	Ice storage	Simulation	No	Considered	Modified Storage Priority	5 – 20 %	Cost
						Chiller Priority Control	20 – 30 %	
	(Perez, Beltran, Aparicio, & Rodriguez, 2013)	Not mentioned	Simulation	Solar	Considered	Subtraction strategy	1.5 – 4.4%	Cost
	(Powell, Cole, Ekarika, & Edgar, 2013)	Chilled water tank	Simulation	No	Considered	Equal ratio chiller loading	6.8 – 9.4 %	Energy
							12.7– 17.4 %	Cost

						With static optimization	0.4 – 1.8 %	Energy
							6.8 – 10.6%	Cost
	(Kim, 2013)	Chilled water tank	Simulation	No	Considered	Storage Priority	6.6 %	Cost
					Not considered		6.4 %	
	(Lefort, Bourdais, Ansanay-Alex, & Guéguen, 2013)	Battery	Simulation	Solar	Considered	No battery, PI controller for temperature	52 %	Cost
	(Z. Zhang, Li, Turner, & Deng, 2011)	Chilled water tank	Simulation	No	Not Considered	Constant charging time	2.3 %	Cost
	(Halvgaard et al., 2012)	TES Tank	Simulation	Solar	Not Considered	CL	25-30%	Cost
	(Morgan & Moncef, 2010)	Ice Storage	Real Building	No	Considered	Storage Priority	0 %	Cost

	Reference	**Type of storage**	**Type of experiment**	**Renew. Energy**	**Weather Pred. Mismatch**	**Compared control**	**Savings**	**Criteria**
Active BITES	(Ren & Wright, 1997)	Hollow core ventilated slab	Simulation	No	Considered	Thermostat	4 %	Cost
							-29 %	Energy
	(Ihm & Krarti, 2005)	FHS	Simulation	No	Not considered	Proportional controller on air temperature	22-30 %	Energy
	(Prívara, Široký, Ferkl, & Cigler, 2011) - (Široký, Oldewurtel, Cigler, & Prívara, 2011)	Ceiling heating system	Real building	No	Considered	WCC	17-24 %	Energy
						Preheating during the night	15-28 %	Energy

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	(Dong & Lam, 2014)	FHS	Exp. Building	No	Considered	Night set-back	30.1 %	Energy
	(Salque, Marchio, & Riederer, 2014)	FHS	Simulation	GSHP	Considered	Thermostat (air temperature)	6 %	Energy
						Thermostat (floor surface temperature)	17 %	
	(Sturzenegger et al., 2016)	TABS	Simulation	No	Not considered	Rules based controller	17 %	Energy
	(Feng, Chuang, Borrelli, & Bauman, 2015)	Cooling radiant slab	Simulation	No	Considered	Rules based controller	14.4 %	Energy
	(Killian, Mayer, & Kozek, 2016)	TABS	Simulation	No	Not considered	Rule-Based PID	0.4 %	Energy
	(Cho, Hong, Li, & Zaheeruddin, 2012)	FHS	Exp. Chamber	No	Not considered	Constant set-point	12.5 %	Energy
						WCC	6.7 %	
	(Masy et al., 2015)	FHS	Simulation	No	Not considered	Intermittent heating	33 %	Energy
Passive BITES	(X. Li & Malkawi, 2016)	Thermal mass	Simulation	No	Not considered	Night set-back	15-40%	Cost
Active storage + active BITES	(Mayer, Killian, & Kozek, 2016)	TABS and chiller storage	Simulation	GSHP	Not considered	PID control	47 %	Cost
Active storage + passive BITES	(G. P. Henze, Felsmann, & Knabe, 2004)	Passive	Simulation	No	Not considered	Chiller priority control	20 %	Cost
		Active					20 %	
		Passive and active					46 %	
	(Hajiah & Krarti, 2012a, 2012b)	Ice storage and thermal mass	Simulation	No	Not considered	Constant temperature set-point	16 – 28 %	Cost
						Chiller priority control	7 – 20 %	
			Simulation	No		Night set-back	33 %	Cost

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	(Liu & Henze, 2006b)	TES Tank and thermal mass	Not considered	Storage-priority - night set-back	26 %	
				Learning control	26 %	

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To understand results better, some authors 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 on MPC performance as (Henze & Krarti, 2005) for passive BITES and (Gyalistras & Gwerder, 2009) for TABS. However, this type of multi-case studies has not been conducted for energy storage systems with active charge.

Furthermore, Table 1 evidences the considerable diversity of comparative basis concerning the controller. This multiplicity makes comparisons between results of studies difficult. One may find it suitable to compare results to the Performance Bound MPC (Gyalistras & Gwerder, 2009). The Performance Bound MPC is also sometimes called “perfect MPC” (Yudong Ma, Matusko, & Borrelli, 2014), “optimal MPC” (Kim, 2013) or “optimal policy” (Kircher & Zhang, 2015). It is an “idealized” MPC, which creates a perfect agreement between predictions and reality (model of the building completely accurate and perfect weather and occupancy predictions). An example with weather predictions is given in Figure 4. The concept behind this controller is to define a benchmark and to compare the performance of other MPC (or the other controllers). Obviously, results of all tested controllers on the same building model will be worst, considering it is not possible to achieve better results compared to a MPC with perfect agreement between predictions and reality. However, the difference between the performance bound MPC results and another control results gives an idea of the performance of the tested controller.

2.1.4. Renewable Energy Penetration

A Model Predictive controller may help to increase the renewable energy penetration. Zong et al. (2012) suggested to use MPC in an office building equipped with many sensors and detectors to increase the direct use of wind energy. They asked occupants to adjust a desired temperature set-point range. The choice of the temperature set-point by the controller was defined as a function of the predicted wind production (when the wind production is low, the controller sets the temperature set-point at the lower limit of the defined range; when the wind production is high, the controller sets the temperature set-point at the higher limit of the defined range). Calculated temperature set-points were after sent to the MPC algorithm. They performed three days of experiment with a predictive horizon of 15 hours. The indoor air temperature was kept in a small range (19°C-20.5°C) without consumption from the grid during around two periods per day (period of around 2 hours). For increasing the renewable

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energy usage too, Mayer et al. (2016) suggested a Model Predictive controller in a building with cooling TABS supplied by a geothermal source and a fan coil system supplied by a chiller and a cold water tank. Compared to the result with a PID controller, they observed an increase in the use of renewable energy of more than 50 %.

In summary, MPC proved having a high potential for improving the performance of buildings with storage systems in terms of thermal comfort, peak demand, total energy cost or renewable energy penetration. Nevertheless, these conclusions have to be qualified due to the large discrepancy of the results and the lack of real case studies. 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.

2.2. Challenges of MPC Implementation

MPC challenges for building with storage system may be categorized into two main topics: the cost of the modeling and optimization of a building with storage and the consideration of uncertainties.

2.2.1. Building Modeling and Optimization Process

MPC is based on a building model that predicts loads and production for renewable energy utilization. Even if the modeling is a more complex issue at the community level (Talebi et al., 2016), modeling a building is a time-consuming process. Cigler et al. (2013) reported that 50% of time spent setting up a model predictive control is for model development (design of model structure, identification, model validation…). This proportion rises to 80% in an industrial implementation (Cigler et al., 2013). By adding a storage system, the required time may increase further. This 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 former is time-consuming. Moreover, the parameter estimation results highly depends on the data set (as for black-box model),

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whether it be a theoretical data set or a measured one (Sourbron, Verhelst, & Helsen, 2012).

- A white-box model, based only on a physical model, is time-consuming to validate, with often 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 mainly uses software having no optimization process like TRNSYS or EnergyPlus does. 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 & Huh, 2016; Kwak, Huh, & 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, charging/discharging and from which source (grid or renewable energy). Since the number of subsystem 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.

2.2.2. 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 (energy consumption and/or thermal comfort). For buildings, the accuracy of some predictions is low (particularly solar radiation and occupancy). Therefore, the controller may receive

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inaccurate information, leading to incorrect actions that may cause some thermal discomforts.

In practice, the effect of uncertainties may be quantified by the difference of results between the deterministic MPC and the performance bound MPC presented previously (idealistic controller considering the same weather and occupancy data in the building model and the "real" simulated building). According to IEEE (2011), a deterministic control application does not consider any variability in the response. Correspondingly, deterministic MPC (called also sometimes "Certainty Equivalence" (Gyalistras & Gwerder, 2009)) considers weather/occupancy predictions but not consider in the control algorithm that predictions may be inaccurate (in contrast to stochastic MPC defined later). Figure 4 shows an example regarding the difference in the consideration of weather data in deterministic MPC and Performance Bound controller. On one hand, as explained previously, a performance bound MPC is an idealistic MPC considering no mismatch between the building model and the "real" simulated building. Therefore, it uses the same weather data in the controller and in the "real" simulated building to achieve the best theoretical results. On the other hand, deterministic MPC inputs a weather forecast with uncertainties in the controller and historical weather data to the "real" simulated building.

Some researchers have studied the effect of uncertainties on the MPC performance 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 & Gwerder, 2009). Considering the controller prediction process, ambient temperature error does not have a major impact on the thermal comfort and energy performance (Ren & 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 most of earlier studies, occupancy was modeled in a simple manner, with occupancy schedules. However, occupancy has

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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. For more information, challenges of occupancy-based MPC have been widely analyzed by Mirakhorli & Dong (2016).

To conclude, MPC has been widely studied and may provide benefits for thermal comfort, energy consumption, peak demand, energy cost and renewable energy penetration. 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 MPC formulations have been suggested as follows.

3. MPC Formulations Developed to Resolve Previous Issues

To solve these challenges, new formulations have been developed that may be divided into several categories:

- Building model simplification
- Appropriate choice of MPC elements
- Optimization time reduction
- Approaches without Real-Time MPC

} *To resolve building and optimization issues*

- Consideration of uncertainties in the controller → *To resolve uncertainty issues*

3.1. Building model simplification

As explained previously, the development of an accurate model to predict the load profile is time-consuming (Široký et al., 2011), thus much effort has been made to find the best compromise between model accuracy and required time for model development (Li & Wen, 2014). For the

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particular case of predictive control in buildings, prediction models have been reviewed (Privara et al., 2013).

For the specific case of a building integrated with storage system and predictive control, several techniques of building modeling simplification, and particularly modeling of the storage system in the building, may be found in the literature as; linearization of the storage model (Berkenkamp & Gwerder, 2014; Deng et al., 2015); simplification of the amount of input data (as an example, no consideration of solar and internal gains (Sourbron et al., 2012) in a building with TABS); and creation of several models (i.e. multi-model MPC) instead of only one complete building model. This last possibility is the focus of the following part.

For buildings with storage systems, multi-model MPC may be performed in several ways. First, the model of the storage system may be separated from the model of the building. As an example, Beghi et al. (2014) used a white-box model of an ice storage for its MPC. The MPC used input results of an ANN (black-box model) of the building to consider the required cooling loads. This technique may be particularly interesting in the case of a retrofitted building, where historical data may be available and a storage system is added.

A more sophisticated solution is to create several models, which depend on the building operation. Kim (2013) suggested a multi-model MPC for building control with chilled water tank. The concept behind this formulation was to discretize the global operation range in several bounded operation ranges. Fuzzy clustering was applied with the weather forecast and occupancy as inputs and cooling loads as outputs for identifying distinctive local operation regimes. A specific model for each operation range was created from historical data. They obtained a cost decrease of 8% compared to a storage priority control and their results were in close agreement with results from the performance bound MPC (around 3%). Similarly, Killian et al. (2016) suggested to create several linear models which change according to the season of the year for each zone of their building. Therefore, each zone had three different models (one for winter, one for summer and one for the transition season).

Finally, Negenborn et al. (2008) suggested to develop several models depending on the prediction horizon length. They suggested to implement two different models with two different prediction horizons and accuracy for a building with thermal and electrical storages. Considering that an event has more influence in the short-term than the long-term, they decomposed the prediction horizon

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into two phases: on one hand, the first phase has a more detailed model with a shorter time step (15 minutes); on the other hand, the second phase has a more simplified model with a longer time step (1 hour). They investigated the effect of varying the proportion of the phase 1 compared to the phase 2 during the prediction horizon on the energy performance and computation time. Results were compared with the complex model one only. As an example, considering the simplified model for the last 20% of the prediction horizon (i.e. considering the simplified model for the most distant events) allows a significant decrease of the computation time (around 80%). At the same time, the energy cost performance decreased only by less than 1%. These studies showed that the computation time can be reduced with multi-model MPC, however, the development of the multi-model MPC may be complicated and time-consuming.

3.2. Appropriate Choice of MPC Elements

As explained in Section 1.3, MPC is based on several elements, mainly prediction horizon, time step, manipulated variables and optimization algorithm. An appropriate choice of these elements may decrease the computation time. Review of optimization algorithms and their impact was carried out by Shaikh et al. (2014) for buildings and by Wang & Ma (2008) for HVAC systems. Some studies on the choice of these elements have already been conducted for building with storage system as the effect of the optimization algorithm by Ihm & Krati (2005) and Ooka & Ikeda (2015) and the effect of the time step by Lefort et al. (2013). Therefore, only the prediction horizon and manipulated variables are studied here since they have not been reviewed yet and they are probably the elements that are more influenced by the presence of a storage system.

Prediction horizon: Prediction horizon is often set equal to 24h in the case of buildings but it may not always be the best choice. Consequently, some researchers have studied the impact of different prediction horizons:

- *With a building with passive BITES:* Cole et al. (2014) studied the effect of the prediction horizon on the controller performance in building with only the building envelope as thermal storage. A reduction of the prediction horizon from 24h to 12h resulted in an increase of 0.9% in peak demand, and a decrease of 2.1% in the energy consumption, respectively, which is insignificant. Oldewurtel et al. (2012) showed that the required prediction horizon depends on the building thermal mass and its HVAC system. Their study reported that a prediction horizon of 24 hours is sufficient in most cases to yield results within 5% of the performance bound MPC. The longest recommended prediction horizon was 38 hours for the average Swiss building with

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TABS. Based on this study, and with a building similar to the previous one, Sturzenegger et al. (2016) increased its prediction horizon to 58 hours. Therefore, the prediction horizon should be chosen as a function of the building thermal mass, i.e. is directly related to the time constant of the building.

- *With an active storage system:* Halvgaard et al. (2012) studied the effect of the prediction horizon on the controller performance in various houses with solar panels and hot water tank. Their study showed a prediction horizon longer than 24 hours does not increase savings. Kummert et al. (1999) studied the effect of the prediction horizon (from 8 hours to 24 hours) in an office building with a hot water tank. An improvement of the thermal comfort was observed with the increase of the prediction horizon (particularly between 8 and 20 hours).
- *With renewable energies*: Prediction horizon mainly depends on the type of renewable energy system. For wind energy, uncertainties are significant and the production is predicted with difficulties. Therefore, a shorter prediction horizon than for conventional building with storage may be used (as 4 hours (Li et al., 2013)). In contrast, in the cases of storage systems linked to solar energy systems, solar energy production is easier to predict and it may be interesting to consider several days in the prediction horizon for storing enough energy before a cloudy day. 48 hours may be a suitable horizon in these cases (Candanedo & Athienitis, 2011).

It may also be possible to use several prediction horizons for different objectives/applications. For example, May-Ostendorp & Henze (2013) chose two time horizons of 24-h and 72-h for control and cost, respectively, allowing impact of future days disturbances to be considered. In summary, the prediction horizon has to be chosen with attention to the system under consideration to find the optimal trade-off between energy/comfort performance and computation time.

Manipulated variables: Manipulated variables may have a great influence on the computation time of the controller. With the addition of a storage system, the number of possible manipulated variables increases, increasing the possibilities number and thus the computation time. To overcome this issue, some studies suggested to limit the number of manipulated variables. Berkenkanp & Gwerder (2014) suggested to select a limited number of operating modes such as a specific mass flow rates and inflow temperature of the thermal storage. Li & Malkawi (2016) used building temperature set-point as manipulated variables. They suggested to use only the cooling temperature set-point instead of both heating and cooling temperature set-point in a commercial building. Consequently, the heating temperature set-point was defined as a function of the cooling temperature set-point (3 degrees lower). Moreover, the temperature set-point is optimized only between 4 a.m. and 10 p.m.

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These simplifications allowed a reduction of the computational time by 96 %. Finally, Ma et al. (2012) suggested optimizing based only on the operation and schedule of the cooling system. Thermal storage tank operating modes were predetermined as function of the chilled water flow rate and the water flow rate demanded by the building.

In summary, the choice of some MPC elements may be a simple way to decrease the computational time. To go further, some studies suggested new MPC formulations to reduce the computation time, for example by considering several control algorithms or without real-time dynamic optimization.

3.3. Consideration of Several Control Algorithms

Schirrer et al. (2016) suggested to decompose the control algorithm into several modules - called modular MPC. Consequently, each sub-problem is simpler and is solved more efficiently. In their study, in a building with a floor heating system, they suggested to decompose it into three modules for the controller algorithm: a first module simulated the building under predicted occupancy and weather conditions. This first module provided the baseline response of the building. Outputs of the model (indoor air temperature and energy demand) were sent to the second module that solves a linear time invariant MPC problem. This algorithm adjusted the energy demand as a function of the given objective function. Finally, the third module calculated the temperature set-point trajectory for the TABS as a function of the optimized energy demand calculated in the second module. All other studies found in the literature implement a distributed or hierarchical MPC as exposed in the following sections.

3.3.1.Centralized / Decentralized / 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

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problem, one solution is to build a distributed MPC, a hybrid MPC mixing decentralized and centralized MPC.

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 5.
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, the storage use, and sometimes the renewable energy consumption (Chandan et al., 2012; Cole et al., 2014; Larsen, Van Foreest, & Scherpen, 2014; Y Ma et al., 2012; Patel, Rawlings, Wenzel, & Turney, 2016). Compared to single building studies, the question of the distribution system is added.

For a single building integrated with energy storage, 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) suggested 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. The13th 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 TABS's temperature. A cooperative iteration-loop is proposed, adjusting results of each MPC as a function of the others.

3.3.2. Hierarchical MPC

Most of the studies found in the literature 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-

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point for passive BITES, storage temperature set-point or operating modes of the storage for active storage system or 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. Figure 6 presents various hierarchical MPC with storage systems. In what concerns the integration of a storage in building, the hierarchical MPC may be divided into three categories depending on their high-level controller's goal: optimization of the heating/cooling system energy consumption, optimization of the storage system, and energy exchange between them.

3.3.2.1. Optimization of the heating/cooling system

Some studies optimized first heating/cooling system variables. Ferrarini et al. (2014) suggested a hierarchical MPC of a building with renewable energy and a battery. The high-level MPC controlled the heating/cooling system variables of the building to decrease the energy consumption while keeping the system within acceptable thermal comfort. To realize this task, the MPC was linked to an estimator of RES production. The building power consumption calculated by the high-level MPC was sent to the low-level MPC, which controlled the battery. The goal was to maximize the self-consumption of renewable energies.

3.3.2.2. Optimization of the Storage System

Some studies first optimized storage system variables. Ren & Wright (1997) performed a study in a building with a ventilated slab. They suggested 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. As a consequence, the low-level controller stopped or started the heating/cooling

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and the heat recovery system following the defined temperature set-points. Similarly, Deng et al. (2015) suggested control an active TES with a high-level controller and to control s chiller plant with low-level controller. First, a dynamic-programming-based algorithm calculates the optimal TES profile as a function of the predicted cooling load and the electricity rates. Then, the TES operation profile is sent to a MPC that optimizes the chiller consumption. Finally, 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.

3.3.2.3. Allocation between Systems

Finally, some studies optimized first the allocation between systems (i.e. when each system will work). Touretzky & Baldea (2014) suggested a hierarchical MPC in a building with a chilled water TES. The high-level MPC optimized the indoor temperature set-point (for the passive BITES) and the operating modes (charging – cooling – charging and cooling – discharging and cooling). The low level controller tracked the indoor temperature set-point in modifying the cooling system variables to ensure an acceptable thermal comfort. A similar structure was followed in Touretzky & Baldea (2016) with a TES system with PCM. Similarly, Fiorentini et al. (2015) suggested a two-level controller in a building with PVT generation system and a PCM thermal storage. At one hand, the high level controller chose the system-operating mode (direct use of the PVT energy, discharge of the storage or direct supply by the cooling system). On the other hand, the low level controller optimized component variables as a function of the chosen operating mode (fan speed of the PVT or PCM storage level for example). 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. Finally, Lefort et al. (2013) suggested a different multi-level MPC. Instead of separating storage and building indoor temperature control, they separated based only on the prediction horizon. The high-level MPC optimized the power at each time step required from each component (grid, battery or solar panel). Optimal powers were sent to the low-level controller that

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used the same optimization algorithm but with a shorter time horizon (equal to the time step of the high-level MPC). The low-level controller defined the optimal control variable values to ensure a good thermal comfort and consume the power calculated by the high-level MPC.

In sum, a high number of studies suggested to use hierarchical MPC. This type of formulation allows systems with different time lag and requirements to be separated and increase the robustness of the controller in considering different prediction horizons. Therefore, a significant decrease of the computation time may be achieved.

3.4. Approaches without Real-Time Dynamic Optimization

To decrease the computational time, some authors 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 strategies of supervisory controls have been developed:

- ***Pre-computed tables:*** Coffey (2012) suggested pre-computed offline MPC with various conditions to build tables that are used during the operation of the building. Kim (2013) also used offline optimization in his study with multi-model MPC (each local MPC is built for a single operation regime). He computed, offline, the optimal policy of each model that was established. To create the final online control, some models are chosen as a function of the forecasted operation regime. The final online control output is then a mix of optimal policy of the selected models. He then estimated the shortened computational time by around a factor of 24 compared to a single-model MPC. Finally, Vidrih et al. (2016) suggested pre-computed matrixes for a MPC to increase the efficiency of free-cooling by enhanced night-time ventilation. If the control matrix may be used for various climatic conditions, it has to be developed for each building to take thermal response of the building into account.
- ***Affine function:*** Klauco et al. (2014) used pre-computed MPC data to create a piecewise affine function.
- ***Decision tree:*** May-Ostendorp & Henze (2013) developed a rule extraction process. The concept behind this solution was to develop, train and test rules on an offline MPC, and then apply them to a building. The result is a decision tree. This form of learning is easily readable even to non-experts and can be described easily. They concluded that results were highly dependent on the variability of internal gains and on the forecast uncertainty.

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Finally, offline MPC may be applied to initialize a controller based on a learning process. Liu & Henze (2006a, 2006b) suggested 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.

3.5. Consideration of Uncertainties in MPC

As shown earlier, uncertainties on weather and occupancy predictions may cause thermal comfort issues particularly in the case of passive discharge systems. Several MPC formulations have been developed, taking uncertainties into account.

3.5.1.Stochastic MPC and Randomized 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

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distribution (Prandini, Garatti, & Lygeros, 2012). For building and storage systems, weather forecast distribution is often presented by a Gaussian function (X. Zhang, Schildbach, Sturzenegger, & Morari, 2013).

- Randomized MPC, and 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 and a deterministic MPC with the storage system was not studied to allow a comparison of the randomized MPC for active storage.

Finally, stochastic MPC may also consider RES production uncertainty. For an underestimation of the production of renewable energy, the energy surplus may be sold to the grid or may be lost due to a full storage system. Conversely, in the case of overestimation, the storage system may not have enough energy to satisfy the demand, involving particularly a higher consumption during peak periods. Therefore, the treatment of uncertainties depends on the selling price of the renewable energy. In the case of a selling price equal or higher than the purchase price, it seems preferable to underestimate the production. This strategy was applied by Li et al. (2013) where the storage system was able to ensure a slight underproduction compared to the production prediction to avoid high peak consumption. As a consequence, the storage system was always a little more charged than the optimal state-of-charge to be able to provide energy in case of an underproduction.

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

3.5.2.Adaptive MPC

The second possibility for incorporating uncertainties is using an adaptive process. Schmelas et al. (2015) suggested 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, Feldmann, Wellnitz, & Bollin, 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 optimization algorithm and thus may increase the controller cost and its computation time.

4. Conclusion and Future Work

Energy storage systems play a crucial role in decreasing building energy consumption during peak periods and expanding the use of renewable energies in buildings and communities. To have a high system performance, the energy storage system has to be properly controlled while maintaining a comfortable thermal environment for the occupants. As a result, the decision process should be able

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to predict both loads and renewable energy production in order to increase the storage system efficiency. This necessity explains the increasing interest during the last decade for predictive control, i.e., control system considering the forecasting.

Several predictive control strategies have been proposed in the literature, as mainly model-free control strategies and MPC. From the one end, promising results using model-free control strategies have been reported and they are particularly simple and cheap to implement. However, at the moment, there is a lack of real case studies and of studies on peak shaving. Moreover, thermal discomfort issues may be observed.

To the other end, a high performance in terms of thermal comfort, peak demand, total energy consumption, total energy cost and renewable energy consumption has been reported in the literature using MPC, explaining the high number of research work carried out over the past decade. However, a large discrepancy in the results have been observed because its performance depends on many parameters. Moreover, most of the research are simulation based and thus some results, especially in terms of thermal comfort, may be qualified since weather predictions uncertainties are often not considered and occupancy and model mismatch are almost never considered. Finally, the significant required computation time and the necessity of modeling the building with its storage slow the MPC usage down.

With regard to the computation time issue, some authors proposed highly promising solutions, as multi-model MPC, distributed MPC or approaches without real-time dynamic optimization. Coupled to the improvement of the computation capabilities, the computation time issue becomes bridgeable. However, some of these approaches increases the time required to set up the MPC before its implementation, increasing the building modeling issue. Therefore, MPC implementation remains highly restrained by the building model requirement often too expensive to be widely used.

Therefore, from the author’s perspective, current limitations and future works of predictive controls depend on the type of buildings:

- For complex new building, the current increase of the Building Information Modeling (BIM) use may help to decrease the building modeling cost. Consequently, a high number of the suggested new formulations to decrease the online computation cost may be particularly interesting. Future studies have to continue the work on the interoperability between BIM and energy modeling softwares (Prada-Hernández, Rojas-Quintero, Vallejo-Borda, & Ponz-Tienda, 2015) and on the coupling of energy modeling software and optimization softwares.

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- For smaller buildings or retrofitted building, these strategies for MPC may not be the solution. Considering for example a widespread residential application, the creation of a building model and the implementation of an optimization process, as simple as they may be, will always stay expensive. As a consequence, future work has to be realized on predictive control without building model. Focus should be on learning processes.

In both cases, interaction between grid and renewable energy system at the building level and not only district level should be deeper studied, and more applications on real buildings have to be realized to study their robustness to uncertainties. Finally, required time to set up the proposed controllers should be checked more often to be able to discuss of its interest regarding the ratio between its cost and its performance.

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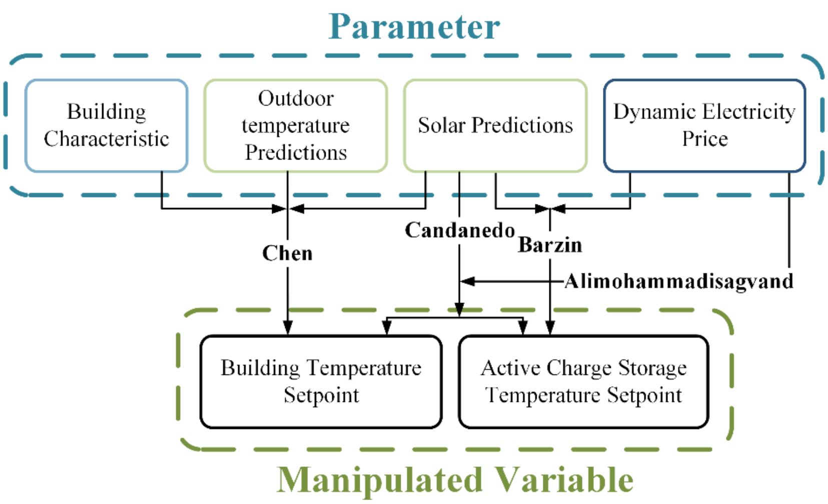

Figure 1: Difference in considered parameters and manipulated variables in parametric control strategies

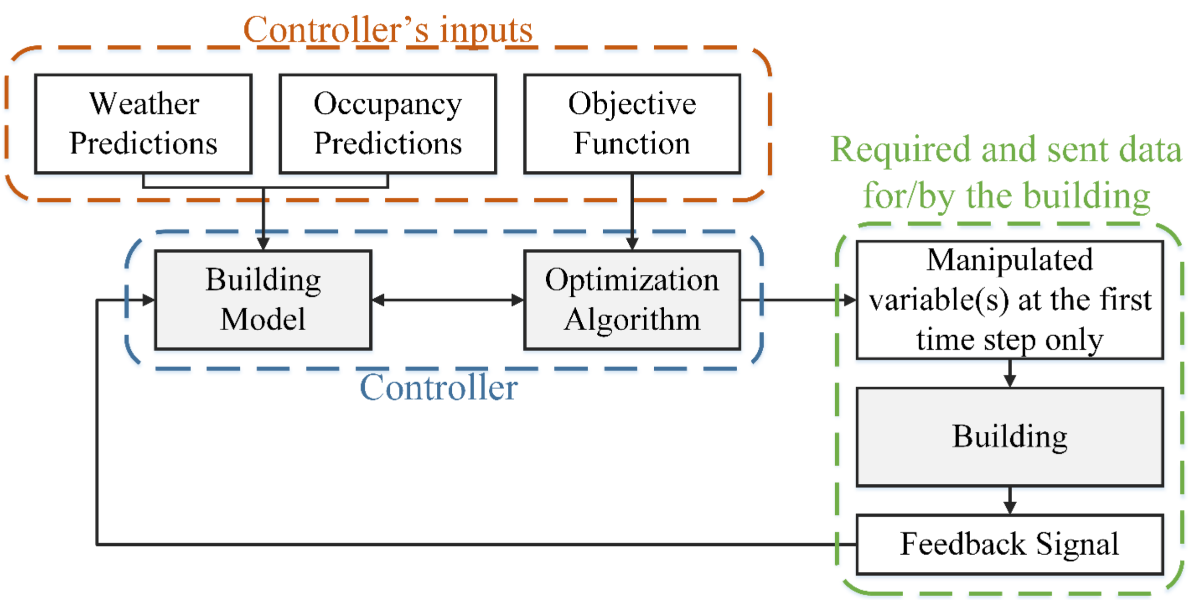

Figure 2: Model Predictive Control for building applications

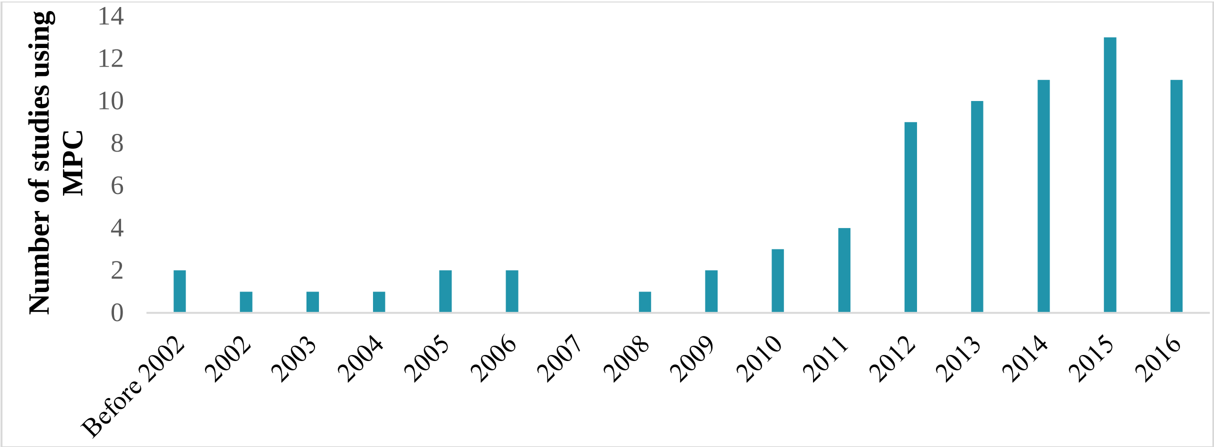

Figure 3: Evolution of the publications number about MPC applied to single building with storage system

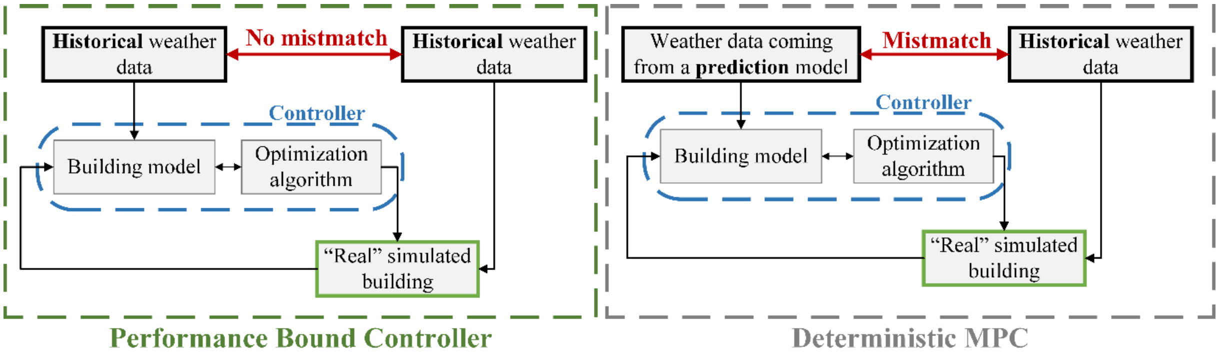

Figure 4: Difference between Performance Bound Controller and Deterministic MPC regarding the weather data

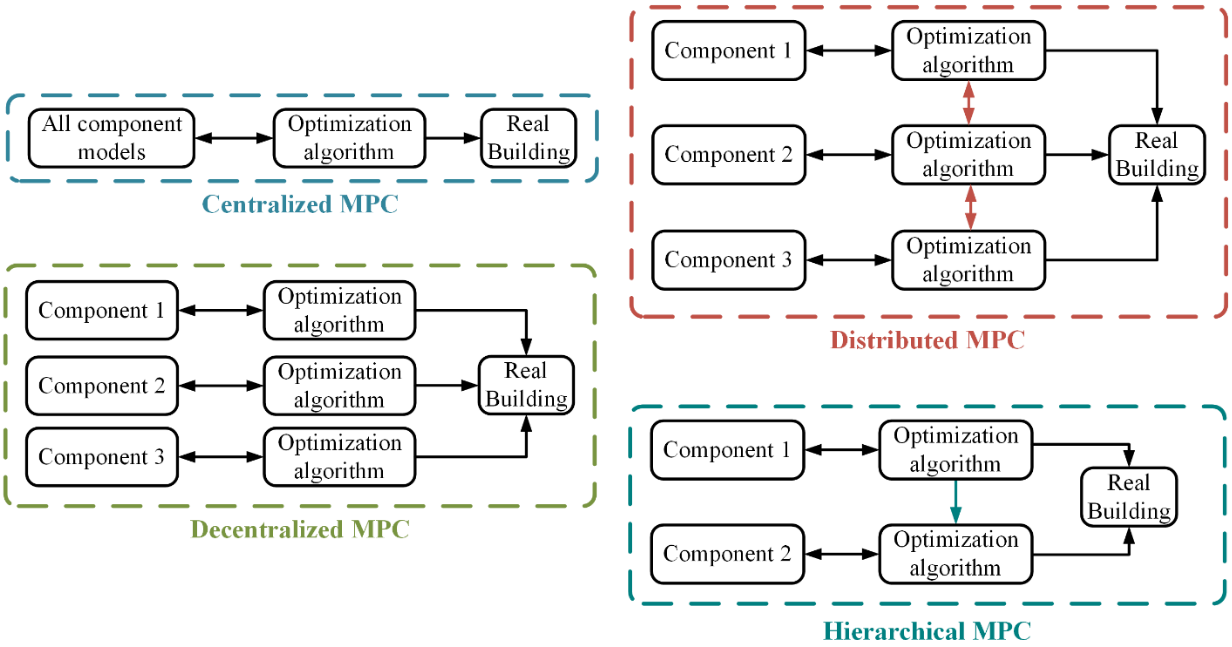

Figure 5: Differences between Centralized, Decentralized and Hierarchical MPC

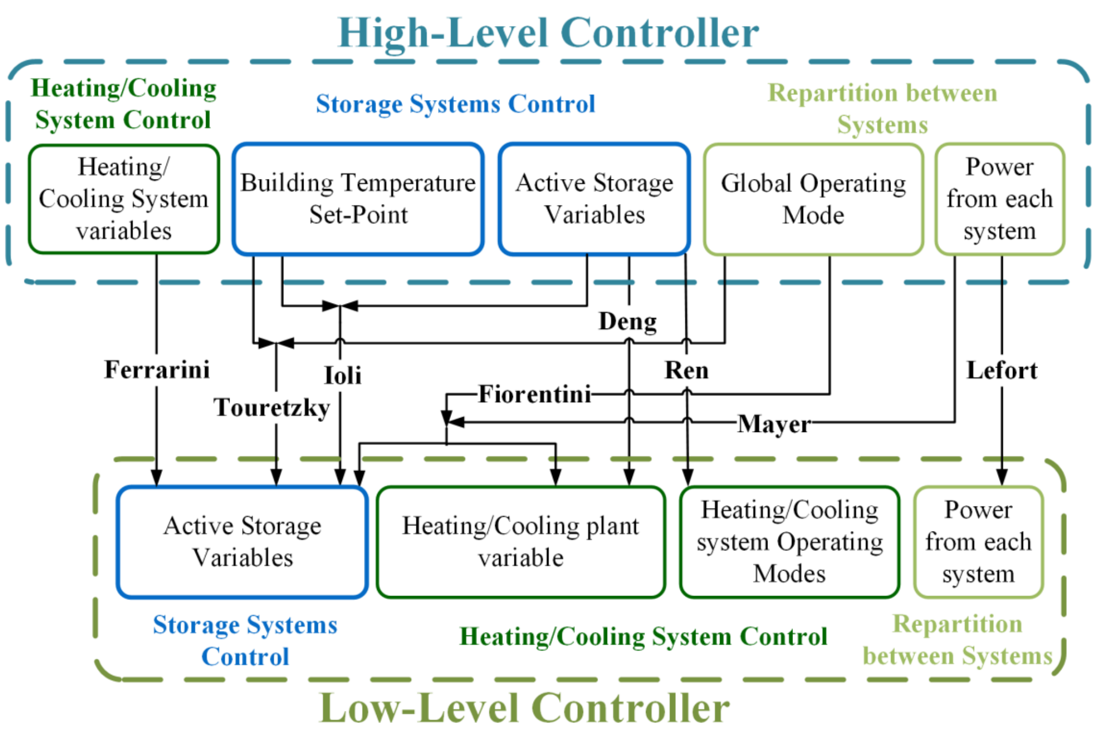

Figure 6: High and low-level controllers as function of the considered manipulated variables