Control strategies for building energy systems to unlock demand side flexibility – A review

John Clauß[1,*], Christian Finck[2], Pierre Vogler-Finck[3], Paul Beagon[4]

[1]Norwegian University of Science and Technology, Trondheim, Norway

[2]Eindhoven University of Technology, Eindhoven, Netherlands

[3]Neogrid Technologies ApS / Aalborg University, Aalborg, Denmark

[4]Energy Institute, School of Mechanical Engineering, UCD, Dublin, Ireland

[*]email: john.clauss@ntnu.no

Abstract

Conventional key performance indicators (KPI) assessed in building simulation lack specific measures of how the building interacts with the grid and its energy flexibility. This paper aims to provide an overview of specific energy flexibility performance indicators, together with supporting control strategies. If applied correctly, the indicators help improving the building performance in terms of energy flexibility and can enable minimization of operational energy costs. Price-based load shifting, self-generation and self-consumption are among the most commonly used performance indicators that quantify energy flexibility and grid interaction. It has been found that the majority of performance indicators, specific to energy flexibility, are combined with rule-based control. Only a limited amount of specific energy flexibility KPIs are used in combination with optimal control or model predictive control. Both of these advanced control approaches often have a couple of economic or comfort objectives that do not take into account an energy flexibility KPI. There is evidence that recent model predictive control approaches incorporate some aspects of building energy flexibility to minimize operational cost in conjunction with time varying pricing.

Introduction

The transition to a sustainable energy system requires a shift to intermittent renewable energy sources, which call for increased flexibility in the energy system. There is therefore a need for consumers to adopt a more holistic approach to energy use beyond the traditional single building management. Generally, building energy flexibility can be understood as the margin in which the building can be operated while respecting its functional requirements.

Demand side management (DSM) in power systems is a way to overcome potential challenges of the electricity grid, such as balancing the generation and consumption, voltage regulation or high peak loads. Demand response (DR) has been implemented into power grids for decades, with forms ranging from load shedding for blackout prevention, to time-of-use (ToU) rates to reduce system peak load (O´Connell et al., 2014).

According to the Building Performance Institute Europe, future buildings, e.g. termed nZEBs 2.0, should play a significant role in transforming the European energy market, as they become interactive players in balancing the grid by DSM (D´Angiolella et al., 2016). Steadily decreasing prices for communication, sensing and computing devices will make future management systems more affordable and thus open up possibilities of improved controls for DR. The choice or design of an appropriate control strategy can be a challenging task, thus it is important to focus on the appropriate KPIs to ensure desired performance results.

Common control strategies are rule-based controls (RBCs) or model-predictive controls (MPCs). In order to operate the energy system in an efficient way, RBCs typically apply pre-defined set points for temperatures (heating) or CO_2 levels (ventilation system). A MPC often makes use of a simplified model of the building for predicting future states of the system and optimizes the schedule over a sliding horizon according to an objective function, such as the total energy consumption (Ma et al., 2012). More details about MPC theory and applications to building HVAC and comfort/energy management are provided in the extensive reviews by Afram and Janabi-Sharifi (2014), Dounis and Caraiscos (2009), Shaikh et al. (2014) and Li and Wen (2014).

This paper aims to review and classify the control strategies to provide demand side flexibility (DSF). The authors give an overview of applied KPIs and present control strategies for deploying energy flexibility in heating and cooling systems of buildings.

This review includes 45 articles. Major keywords during the literature search were: demand side flexibility, energy flexibility, energy flexible buildings, advanced control, demand response control in buildings. Firstly, the need for energy flexibility and its indicators will be discussed. Secondly, an overview of conventional and specific energy flexibility KPIs is presented. Thirdly, a summary of control strategies aiming to deploy DSF is given and associated KPIs in applications are shown. On top of this, building simulation tools used for specific energy flexibility KPIs are presented considering RBC, optimal control (OC), and MPC.

Background concepts

Introduction to performance data

An effective KPI provides an accurate measure of overall system status, thus facilitating decision making, by quantification and prioritization of resource allocation. A building KPI must be applicable throughout the system's operational lifespan; during all seasons and occupancy levels. KPIs differentiate themselves as both "predictive" and "persistent" (Mauboussin, 2012). Deru and Torcellini (2005) define an indicator as "a high-level performance metric that is used to simplify complex information and point to the general state or trends of a phenomenon." Different performance metric address different audiences:

- Indicators: Policy makers
- Tier 2 metrics: Designers, suppliers & owners
- Tier 1 metrics: Designers, operators & researchers
- Monitor data: Operators & researchers

Monitoring procedures display data, followed by further procedures and analysis to produce higher metrics and indicators. Higher level metrics fit over longer timescales.

Performance *goals* should drive the design of a building to operate towards a desired result. Performance *metrics* measure and track performance towards the performance goals. Effective control maintains or even increases the value of performance metrics despite the abundance of possible monitoring data.

Conventional KPIs of energy efficiency at building level

KPIs for individual building energy efficiency are well covered in the literature. Common performance indicators during operational stage are:

- Final energy use
- Energy needs
- Cost of energy
- Primary energy use
- CO_2 emissions

These conventional KPIs can be however complemented by specific energy flexibility indicators related to services that a building can offer to the grid, as discussed in the following parts.

Demand side flexibility

Energy system flexibility is proposed as one enabler for high levels of renewable energy penetration (Lund et al., 2015). This builds upon the well-established concept of DSM described in seminal work by Gellings and Smith (1989).

Introduction to demand side flexibility

In a literature review by Lopes et al. (2016) several definitions of "flexibility" and methodologies used to quantify the energy flexibility in buildings have been proposed.

The building-to-grid energy flexibility is often reduced to the electricity consumption for heating and cooling. For example, in a cooling regime (such as in California) HVAC systems are a leading demand response resource (Watson, 2013). Some form of storage (typically thermal mass or water storage tanks) is required to exploit the full flexibility potential. As this storage gets activated, it is temporarily loaded to higher (or lower) temperatures. As a result, the total energy consumption is often increased, while operational costs can be actively reduced and a service to the electricity grid can be provided. Common demand management services are load shifting, peak shaving or load balancing. If responsive and reliable at short notice, DSM may potentially support other grid ancillary services, such as spinning reserves, frequency stability or voltage regulation, but often requires electrical or battery energy storage. A battery discharge time has an upper limit and further depends on its charge state at the time when it is directed to discharge. The uncertainty of a battery's charge state disqualifies it from capacity and grid ancillary services according to its detractors (Huntoon, 2016). In terms of load balancing and non-spinning reserves the electricity grid can benefit from an advanced DSM in order to increase renewable generation integration. DSM supports renewable integration primarily by load following and grid frequency regulation; especially if its ramping rates are high (Watson, 2013).

The flexibility potential often depends on the size of the storage. For building engineers and designers, this is crucial because the storage size directly influences the required capacity of the HVAC system as well as the investment costs. As foreseen by Strbac (2008), the economic analysis of energy flexibility is still challenging.

The economic benefits of energy flexibility vary over time and stage in a heating or cooling season. Increased flexibility during winter is quantified in the second example of Stinner et al. (2016) similarly by Pallonetto et al. (2016). Garnier et al. (2015) analyze different seasons of HVAC operation, noting that one source of energy flexibility, building thermal inertia, is low during the summer. That work also found that seasonal variability is one of the reasons that MPC optimizes energy costs compared to RBC.

Practitioners of building simulation tools already use time varying inputs such as weather, outside air temperature and irradiance. Daily energy markets and real time (i.e. hourly or half hourly) pricing introduces electricity pricing as another time varying input to a simulation of a grid integrated building or district. High grid penetration by renewables causes uncertainty in electricity generation due to the weather, especially solar irradiance and wind speed. The predominant uncertainty means that real-time electricity pricing may be analyzed as a stochastic process (Kitapbayev et al., 2013).

Mathematical finance techniques process stochastic inputs in order to quantify the flexibility of a possible investment. One technique, *real options*, is a way to make a business decision. Applied to a demand site equipped with a CHP, the high level control decision is to operate or idle the local power plant in favor of utility supplied energy based on dynamic energy (Kienzle and Andersson, 2009). The decisions rely on Monte Carlo simulation of stochastic energy price inputs into an Energy Hub model.

The "Real options" method exceeds the discounted cash flow valuations, by modelling uncertainty and operational flexibility. Use of simulation requires a time-step, enabling its re-calibration to influence short-term operational control. As shown by Kitapbayev et al. (2015) “short term flexibility can change the long term business case, while the long term investment plan can enable short term flexibility”.

KPIs of energy flexibility

Table 1 provides an overview of KPIs related to energy flexibility. A number of KPIs is presented, together with their formal mathematical definition and context of application. Notations are introduced in the nomenclature at the end of the paper.

Indicators for load matching and grid interaction are gaining importance, particularly for net zero energy buildings. Such buildings produce electricity from on-site renewable energy sources in order to meet the annual zero energy balance. Electricity grids are usually designed to cover the peak demands of the connected buildings, but not for handling peaks from on-site electricity generation. Therefore, considerations about self-consumption of on-site generated electricity is becoming increasingly important (both at design and operation level), especially in countries with a large share of on-site renewable energy sources (Salom et al., 2014a).

Table 1. Overview of the KPIs related to energy flexibility

KPI	Mathematical definition of the KPI	Characteristics	Reference
Self-generation (also known as load cover factor)	Proportion of electrical demand met by on-site generation. $\gamma_l = \frac{\int_0^T min[g(t) - S(t) - \zeta(t), l(t)]dt}{\int_0^T l(t)dt}$ (1) The time resolution often is one hour, often over an annual period.	- Displays daily and seasonal effects caused by different generator types such as PV, CHP. - Comparing control strategies is possible - Accepted by several research groups, such as Annex 52. - Independent of any energy or emission savings by the whole energy system.	(Salom et al., 2014a) (Baetens et al., 2010) (De Coninck et al., 2014) (Vanhoudt et al., 2014) (Salom et al., 2014b) (Klein et al., 2015)
Self-consumption (also supply cover factor)	Proportion of on-site generation consumed by building. $\gamma_s = \frac{\int_0^T min[g(t) - S(t) - \zeta(t), l(t)]dt}{\int_0^T g(t)dt}$ (2)		
Peak power generation	Peak value of the on-site generation normalized by the designed grid connection capacity (E_{des}). $\bar{G} = \frac{max[g(t)]}{E_{des}}$ (3)	- Provide boundaries to load duration curves and carpet plots. - Identify the load or generation peak periods. - Comparisons to the net export and net imports respectively.	(Salom et al., 2014a)
Peak power load	Peak value of the demand normalized to the nominal designed grid connection capacity (E_{des}). $\bar{L} = \frac{max[l(t)]}{E_{des}}$ (4)		(Salom et al., 2014a)
Flexibility (optimum cost)	The maximum reachable load is sum of all controllable loads. Maximum and minimum load (l), lead to a positive or negative flexibility (Φ) (possibility of increased or decreased power consumption, respectively) during an interval (t). $\Phi_{pos} = l(t)_{max} - l(t)_{ref} \geq 0$ (5) $\Phi_{neg} = l(t)_{min} - l(t)_{ref} \leq 0$ (6) Relative costs (Γ) vary due to total cost J_c. $\Gamma_{max} = J_{c,max} - J_{c,ref} \geq 0$ (7) $\Gamma_{min} = J_{c,min} - J_{c,ref} \geq 0$ (8)	- Solves several optimal control problems - Reference scenario optimally controls for thermal comfort and operational costs - Aggregatable and comparable to various buildings, climates and energy systems (incl. renewables) - Instantaneous cost curves vary over time-steps and boundaries.	(De Coninck and Helsen, 2016)
Flexibility factor FF_{PC} (costs)	In terms of procurement costs (PC) avoided. $FF_{PC} = \frac{PC_{max} - PC}{PC_{max} - PC_{min}}$ (9) Dar et al. (2014) call it relative import bill (RIB).	- Annual PC varies due to electricity time of use (ToU) tariffs. - FF maximizes as PC → PC_{min} if all heating is done during cheapest ToU.	(Dar et al., 2014) (Masy et al., 2015)
Flexibility factor FF_{shift} (volume)	In terms of energy shifted compared to a reference profile. $FF_{shift} = \frac{FF_{PC} - FF_{PC,ref}}{FF_{PC,ref}}$ (10)	- $FF_{PC,ref}$: flexibility in terms of PC for a flat tariff reference case	(Masy et al., 2015)
Flexibility factor (FF)	Ability to shift the energy use from high to low price periods: $FF = \frac{\int_{LPT} l_{heating}\, dt - \int_{HPT} l_{heating}\, dt}{\int_{LPT} l_{heating}\, dt + \int_{HPT} l_{heating}\, dt}$ (11)	- Gives a quick indication of when heating energy is consumed - FF = 0 if demand is similar during both price periods - FF = 1 (max) or -1 (min), if demand in single pricing period	(Le Dréau and Heiselberg, 2016)
Load shift for CO_2	Optimization value function to minimizing carbon emissions: $V = \int_0^T C_{CO_2}(t) \cdot l(t)dt$ (12)	- Requires carbon emissions per kWh for time-steps *t*	(Favre and Peuportier, 2014)

KPI	Mathematical definition of the KPI	Characteristics	Reference
Energy flexibility ε	Amount of flexible energy that could be delivered. $\varepsilon_{forced}(t) = \int_0^{T_{forced}} l_{flex.forced}\, dt$ (13) $\varepsilon_{delayed}(t) = \int_0^{T_{delayed}} l_{flex.delayed}\, dt$ (14)	- *"Forced flexibility"*: charging or heating the TES by a grid connected heater. - *Negative flexibility*: increase generation - *"Delayed flexibility"***:** discharging TES, while grid connected heater is off - *Positive flexibility:* reduce generation - Two other metrics: ramp-up capability (MW/min) and power capacity (MW)	(Stinner et al., 2016)
Available structure storage capacity	Amount of heat that can be added to a building's thermal mass during a predefined charging event, while constrained by thermal comfort. $C_{ADR} = \int_0^T \left(l_{ADR} - l_{ref}\right) dt$ (15)	- A characteristic property of a building, but time varying. - C_{ADR} varies due to boundary conditions of climate, occupant behavior and heating system. - The ADR event starts at a minimum comfort temperature	(Reynders et al., 2015)
Storage efficiency	Fraction of heat that is stored during an ADR event, later used to reduce heating load power to maintain the thermal comfort. $\eta_{ADR} = 1 - \frac{\int_o^\infty \left(l_{ADR} - l_{ref}\right) dt}{\int_0^T \left(l_{ADR} - l_{ref}\right) dt}$ (16)	- Can be seen as a characteristic property of a building - The integral in the denominator equals the heat stored in the storage event or the C_{ADR}	(Reynders et al., 2015)
Shifting efficiency	Heating energy shifted compared to a reference case: $\eta_{shift} = \frac{-\Delta l_{heat\ discharged}}{\Delta l_{heat\ charged}}$ (17)	- Used to characterize the thermal mass as a storage medium - Methodology can also be used for water storage tanks	(Le Dréau and Heiselberg, 2016)
Loss of load probability (LOLP)	Time (%) when on-site generation is less than local demand. $LOLP_b = \frac{\int_0^T f(t) dt}{T} \begin{cases} f(t) = 1, if\ ne(t) < 0 \\ f(t) = 0, if\ ne(t) \geq 0 \end{cases}$ (18) Energy autonomy: $A_b = 1 - LOLP_b$ (19)	- Measures proportion of the year requiring grid electricity imports - Omits the volume of grid imports - Can be used for designing the control of the PV / energy system - Links to energy autonomy (A_b)	(Salom et al., 2014a)
Power shifting capability	Difference between heating power during the ADR event and the reference heating power during normal operation. $l_{shift} = l_{ADR} - l_{ref}$ (20)	- Load/power flexibility of building - Associated metric "power shifting capability" combines l_{shift} and its duration t_{shift}	(Reynders et al., 2015)
Grid feed-in	$Grid\ feed\ in = \int_0^T ne(t) dt$ (21)	- Minimizing grid feed-in increases self-consumption - More efficient than curtailment to achieve grid integration regulation	(Salpakari and Lund, 2016)
Demand recovery ratio	$DRR = \frac{\int_0^T l_{heating}(t) dt}{\int_0^T \min\left[l_{heating}(t)\right] dt}$ (22)	- Quantifies the increase in energy use due to load shifting at the demand side - If ADR = 0, then DDR = 1 (min) - Indicates reduced thermal losses with increasing number of flexible buildings - System level: different temperature set points and storage technologies	(Arteconi et al., 2016)

Flexibility indicators can describe physical characteristics of a building (e.g. storage capacity) or quantify the magnitude of the building´s reaction to external signals (e.g. electricity price) within the context of the power grid. Load matching and grid interaction indicators (e.g. equations 1-4, 18, 21) give a coarse overview of the ratio of the building energy load vs. on-site electricity generation as well as identify the load and generation peak periods. Energy flexibility indicators (e.g. equations 9-11) are often price-based and show whether energy/electricity is consumed during high- or low-price periods. Their generic nature allows their application to various building types, climates and energy systems. All the presented parameters can be used for determining the energy flexibility (or related characteristics) of a building and can either be calculated during post processing of the building simulation results or be included into a model-based control algorithm directly. Limitations of the indicators include the availability of the data used to compute them, so that the simulation software must be able to provide the data.

Control strategies for deploying energy flexibility

RBC strategies are a common approach for controlling energy systems of buildings. They use pre-defined conditions (or decision rules) to change the current state of a system and can easily be implemented into dynamic building simulation tools. Depending on the decision criteria of the RBC (e.g. weather, price, occupancy), it can aim at activating the energy flexibility of the building to improve grid interaction, lower energy costs, perform load shifting or reduce energy needs by varying the temperature set points of the buildings zones or the water storage tanks. RBCs mainly fulfill a certain control objective, but are not designed to achieve optimization of the overall system behavior. Therefore, a balance between different control objectives, such as a low energy consumption and reduced energy costs, but a high load shifting potential has to be found, for instance by advanced control strategies, such as MPC.

Afram and Janabi-Sharifi (2014) point out that advanced control systems (OC, fuzzy logic, MPC) in combination with thermal storages show a great opportunity for peak shaving, hence reducing infrastructure and operational costs. These controls can use external information for minimizing the energy consumption and therefore have a higher potential to fully deploy the flexibility of a building compared to rule-based control. Classical control strategies, such as thermostatic on/off control, PI or PID control are state-of-the-art for HVAC applications and are not able to adapt to time-varying disturbances or changes in environmental conditions (Afram and Janabi-Sharifi, 2014) and thus may fail to provide flexibility in a dynamic manner. A control strategy that enables the flexibility of the HVAC system operation, such as MPC, permits optimization of the energy consumption while preserving or even improving thermal comfort (Afram and Janabi-Sharifi, 2014). Predictive and optimal controls show a great potential for deploying DSF because they can deal with time-varying operating conditions and can interact with the energy system and the grid (De Coninck and Helsen, 2016). In this manner, they have a potential to contribute to peak shaving and load shifting of the electricity consumption (Haghighi, 2013). MPC is seen as one of the most promising developments as it can take into account future weather, electricity price forecasts (including their uncertainties (Oldewurtel, 2011)) as well as occupant behavior when computing an optimal consumption decision. Research at a district scale argues that the value of building energy flexibility depends on time varying energy prices (Kitapbayev et al., 2015).

Energy price data sources are publicly available in a number of countries seeking to improve transparency on the market, which facilitates the use of real world data for building simulations. In particular, data for the Scandinavian markets and neighboring countries is provided by NordPool (Nord Pool Spot, 2016), Energinet for Denmark (Energinet, 2016) and Statnett for Norway (Statnett, 2016). For Ireland, data is available on the single electricity market platform (Single Electricity Market Operator, 2016), and for Britain and the Netherlands data is provided by power exchange (Apx Power Spot Exchange, 2016). Estimations of time-varying CO_2 intensity of the power due to electricity generation are available from the Eco-Invent database (Ecoinvent, 2016).

Compared to RBCs, which are often designed to improve one control objective, MPCs allow the computation of an optimum schedule that can compromise between different control objectives. Several software tools were used in the reviewed articles to assess building energy flexibility. Commonly used tools for building simulation are EnergyPlus (Le Dréau and Heiselberg, 2016), IDA ICE (Alimohammadisagvand et al., 2016) or TRNSYS (Esfehani et al., 2016). These tools apply detailed numerical models for modelling the building energy performance, where RBCs can be implemented easily. If MPC is to be tested in combination with these tools, the optimization problem of the MPC is to be solved in another software, such as MATLAB. Furthermore, an interface, which couples the optimization software and the building simulation software, is required. The BCVTB and MLE+ interfaces were used by Ma et al. (2011) and Garnier et al. (2015), respectively. MATLAB and Modelica can be used for both, modelling the building performance and running the optimization. In Modelica, RC-models (used by Klein et al. (2015)) or component models from different libraries (De Coninck and Helsen, 2016; Reynders et al., 2015) can be applied for building simulation. RC-models lead to simplified building models which express the building properties properly. Halvgaard et al. (2012) used RC-models in MATLAB in order to test an economic MPC.

Table 2 provides an overview of control strategies that have been implemented in building performance simulations to deploy demand side flexibility. All the control strategies are either a RBC, an optimal control or a MPC. The characteristics of each strategy are shown for easier reproduction.

Table 2. Summary of control strategies to deploy demand side flexibility

Building energy control	**Control design consideration**		**Characteristics**	**References**
	LS[1]	ORM[2]	[1]LS – Load shaping, [2]ORM – On-site renewable energy maximization	
RBC (1)	x	x	Increase of 12K in DHW set point caused by three triggers - RBC 1a: time based at 12:00 every day, activating the heat pump - RBC 1b: if the power injection to the grid exceeds a threshold - RBC 1c: if voltage of buildings grid connection exceeds a threshold	(De Coninck et al., 2014)
RBC (2)	x	x	Load shifting takes place if either local PV surplus generation or high proportion of RE in grid electricity - Zone heating curve heating increases by 3K, compared to reference - Zone cooling curves cooling decreases by 3K, compared to reference	(Klein et al., 2015)
RBC (3)	x		Set point of zone temperature responds to ToU pricing - Decreases by 2K during high price period (maximum duration 4-24h) - Increases by 2K during low price period (maximum duration 4-24h)	(Le Dréau and Heiselberg, 2016)

Building energy control	Control design consideration		Characteristics	References
	LS[1]	ORM[2]	[1]LS – Load shaping, [2]ORM – On-site renewable energy maximization	
RBC (4)	x	x	While comfort constrained, a TES coupled heat pump activates for, - *Self-consumption*: If surplus PV electricity generation - *Power-exchange*: PV surplus > limit & TES or space heating possible - *Price based control*: If hourly tariff < specified threshold	(Dar et al., 2014)
RBC (5)	x		- Temperature set point increased by dT_{comf} [K], a set of (1, 2, 3, 4), for a period that ranges from 15 min to 6 h. - Heating load subsequently reduced but minimum comfort maintained.	(Reynders et al., 2015)
RBC (6)	x	x	*Surplus (off peak) scenario*: heat pump consumes surplus grid electricity - DHW and space heating set point deadband of ±2K, 15min time-step - Minimize peak time consumption by 5K DHW set point reduction	(Esfehani et al., 2016)
RBC (7)	x		Price based control called *"Momentary control algorithm":* - Hourly tariff ≤ limit: normal set points of DHW (55°C) and space heating (21°C). TES maximum set point experimented over 55-95°C - Hourly tariff > limit: minimum set points of DHW & space heating. - If heating off, available TES energy heats DHW and space	(Alimohammadisagvand et al., 2016)
RBC (8)	x		- 1) Occupancy set points: 21°C (24°C bathroom), else 18°C - 2) Constant set points: 21°C (24°C bathroom) - 3) Occupancy set points from 1) and overnight TES heating to 55°C for use during peak time of 10:00 - 12:00	(Masy et al., 2015)
RBC (9)		x	- If PV generation surplus, self-consumed by shiftable (inside 24 h) appliances, battery or TES. - PV generation insufficient, battery discharged and deficit from grid	(Salpakari and Lund, 2016)
Optimal control (OC) (1)	x		- Heat pump operation scheduled over 24 h horizon for cost-optimality - Challenging due to heat pump COP non-linearity with temperature - Computation time depends on flexibility (TES, battery or appliances).	(Salpakari and Lund, 2016)
OC (2)	x		- Heat pump operation is optimized by model predictive control for two tariff structures: day/night and ToU spot pricing. - Zone temperatures set point 20-22°C either i) continuously or ii) daily time interval 08:00-12:00. - Control objective is operational costs minimization of the heat pump	(Masy et al., 2015)
OC (3)	x		- Comfort constrained, cost minimization produces a reference plan - Electricity ToU tariffs stimulate consumption deviation from the reference plan during specific intervals in order to minimize cost. - Discomfort cost calculated during occupancy and outside 21.8-23.5°C - Special case of temperature reference tracking about set point	(De Coninck and Helsen, 2016)
Economic MPC (1)	x		- Comfort constrained, electricity cost minimization by heat pump - Heat energy storage of floor shifts consumption to lower tariff periods	(Halvgaard et al., 2012)
Economic MPC (2)	x		- Comfort constrained, energy minimization by HVAC system - Potential for grid frequency regulation by exports of active power - Parameter adaptive building model contains four flexibility variables: air flow and power, both increase and decrease flexibility. - Novel proposal to co-design the control algorithm and HVAC system	(Haghighi, 2013)
Economic MPC (3)	x		- Minimization and shaping of aggregated building electricity demand, by scheduling of residential cooling set points. - Energy systems integration of aggregated building demand with grid	(Corbin and Henze, 2016a)
Economic MPC (4)	x	x	- Shape residential demand profile from grid feeder - Minimization of the deviation from reference demand curves by steps - (1) Compute a reference demand curve aggregated at the feeder level - (2) Disaggregate to a reference demand curve per residence; then modify for renewables generation. - (3) Minimize the difference between the actual residence demand curve and the modified reference demand curve - MPC controllers of each residence adjust the cooling set points depending on their pre-defined boundaries	(Corbin and Henze, 2016b)
MPC (5)	x		- Balances energy consumption and, when applicable, discomfort - Output is an optimal sequence of heating supply temperatures - Patented	(Lindelöf et al., 2015)
MPC (6)	x		- Minimization of energy consumption by a multi-zone HVAC system - Thermal comfort constraints are indicated by predicted mean vote - Artificial neural network schedules both cooling and heating	(Garnier et al., 2015)
Economic predictive control	x	x	- Minimization of heat pump energy costs by shifting its operation to times that match high on-site PV generation	(Kandler et al., 2015)

In order to see the aims of each control strategy, they are distinguished between two control design considerations: load shaping (LS) and maximum use of on-site renewable energy (ORM). Load shaping includes peak shaving and load shifting to off-peak hours.

It can be seen from Table 2, that among the investigated literature, RBC and MPC are both used for load shifting. However, RBC is more often used for achieving a maximization of the use of on-site renewable energy than MPC. This may be due to the easier implementation of RBC into building performance simulations.

Mapping of KPIs with control strategies

Table 3 provides an overview of the reviewed references focusing on combinations of investigated control strategies and KPIs. For most of the respective studies, MPC is used with conventional KPIs, whereas flexibility indicators are used with RBC. This can be due to the greater ease of implementation of RBC strategies in building performance simulations, compared to MPC which is still a relatively new field of research. KPIs can be calculated based on output data available from building performance simulation, thus MPC could easily be used together with specific energy flexibility KPIs.

Conclusion

Key performance indicators measuring energy flexibility are becoming increasingly important for building performance simulations, especially with the inclusion of DSM or time-varying energy pricing. The authors are convinced that model-based control applied to energy flexibility improves a building´s sustainable design and operation. Generally, RBCs as well as OCs and MPCs can have energy flexibility embedded in the control objectives.

The main findings from this paper are:

- Multiple specific energy flexibility KPIs exist, which allow quantifying different aspects of DSF.
- Services covered by energy flexibility KPIs (mainly focusing on the building) do not cover all possible services for DSM such as grid integration or grid ancillary services.
- Most KPIs specific to energy flexibility are found in RBC studies, whereas OC or MPC studies focus mainly on conventional KPIs.
- RBCs are reported as effective, if focused on a single KPI (including conventional and specific energy flexibility KPIs).

Table 3. Overview of KPIs used in control ([1] rule-based control, [2] optimal control, [3] (economic) model-predictive control)

		Controller	
		RBC[1]	**OC[2] and MPC[3]**
KPIs for energy flexibility	Self-generation	RBC (1) (De Coninck et al., 2014) RBC (2) (Klein et al., 2015)	
	Self-consumption	RBC (1) (De Coninck et al., 2014) RBC (2) (Klein et al., 2015) RBC (4) (Dar et al., 2014) RBC (9) (Salpakari and Lund, 2016)	
	Flexibility factor FF	RBC (3) (Le Dréau and Heiselberg, 2016)	
	FF_{PC} and FF_{shift}	RBC (4) (Dar et al., 2014) RBC (8) (Masy et al., 2015)	OC (2) (Masy et al., 2015)
	Flexibility (optimum cost)		OC (3) (De Coninck and Helsen, 2016)
	Grid feed-in		OC (1) (Salpakari and Lund, 2016)
	Available structure storage capacity	RBC (5) (Reynders et al., 2015)	
	Storage efficiency	RBC (5) (Reynders et al., 2015)	
	Shifting efficiency	RBC (3) (Le Dréau and Heiselberg, 2016)	
	Power shifting capability	RBC (5) (Reynders et al., 2015)	
Conventio-nal KPIs	Energy consumption	RBC (6) (Esfehani et al., 2016) RBC (7) (Alimohammadisagvand et al., 2016)	E-MPC (3) (Corbin and Henze, 2016a) E-MPC (4) (Corbin and Henze, 2016b) MPC (5) (Lindelöf et al., 2015) MPC (6) (Garnier et al., 2015)
	Energy costs	RBC (7) (Alimohammadisagvand et al., 2016)	E-MPC (1) (Halvgaard et al., 2012) E-MPC (2) (Haghighi, 2013) OC (1) (Salpakari and Lund, 2016)

- OC and MPC can consider different "objective functions" that optimize the system behavior by taking into account energy flexibility. Moreover, they can be assessed with a broader variety of KPIs beyond the sole objective they focus on.
- Energy flexibility KPIs relying on RBC can be derived rather easily from simulation tools, such as EnergyPlus, TRNSYS or IDA ICE.
- Advanced control strategies including optimization procedures (MPC and OC) typically use simulations in MATLAB and Modelica.

Furthermore, information on grid energy data sources were provided to encourage the use of realistic data in future simulation work. Future research should concentrate on the limitations and robustness of existing energy flexibility KPIs as well as their implementation in OCs and MPCs. Furthermore, development of additional KPIs addressing DSM services towards the power grid is also expected to provide valuable contribution.

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Nomenclature

A_b	Energy autonomy
ADR	Active demand response
C	Capacity
C_{CO_2}	CO_2 intensity of power [$kgCO_2$/kWh]
e(t)	Electricity exported to the grid
E_{des}	Nominal design connection capacity between the building and the grid
f(t)	Binary function indicating net import
g(t)	On-site electricity generation
$\bar{G}$	Maximum electricity generation normalized to E_{des}
i(t)	Electricity imported from the grid
J_c	Energy costs
l(t)	Energy load, e.g. heating power. Optional time step (t)
$\bar{L}$	Maximum electricity load normalized to E_{des}
$LOLP_b$	Loss of load probability of the building
ne(t)	Net exported energy to the grid
S(t)	Energy storage balance
t	Index of observation time-step
T	Time interval under consideration (e.g. year)
V	Objective function for CO_2 emissions

Greek

γ_l	Self-generation / load cover factor
γ_s	Self-consumption / supply cover factor
Φ_{neg}	Negative flexibility
Φ_{pos}	Positive flexibility
Γ_{max}	Maximum relative costs
Γ_{min}	Minimum relative costs
ζ(t)	Energy losses
ε	Energy flexibility
Δl	Load difference

Subscripts

b	Building
des	Design
l	Load
neg	Negative
pos	Positive
ref	Reference
shift	Shifting
s	Supply

Acronyms

COP	Coefficient of performance
DHW	Domestic hot water
DR	Demand response
DSF	Demand side flexibility
DSM	Demand side management
EMPC	Economic model-predictive control
FF	Flexibility factor
HPT	High price time
KPI	Key performance indicator
LPT	Low price time
LS	Load shaping
max	Maximum
min	Minimum
MPC	Model-predictive control
OC	Optimal control
ORM	On-site renewable energy maximization
PC	Procurement costs
RBC	Rule-based control
RE	Renewable energy
TES	Thermal energy storage
ToU	Time-of-use

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