1 Economic impact of persistent sensor and actuator faults
2 in concrete core activated office buildings

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4 **Abstract**

5 Sensor and actuator degradation occurs frequently in office buildings. These
6 can have a large impact on HVAC performance, both on energy use and
7 thermal (dis)comfort. The degree of impact depends on the faulty com-
8 ponent(s), fault type(s) and fault severity and has a significant non-linear
9 relation with the control strategy and comfort constraints. Concrete core
10 activated (CCA) office buildings typically have a high thermal inertia, high
11 comfort requirements and they are equipped with low exergy and low ca-
12 pacity production systems. This allows the inclusion of renewables, thermal
13 storage and flexible load shifting, but this also augments the effects of small
14 perturbations in control output.

15 In this paper, the economic fault impact is investigated by dynamic sim-
16 ulations using an emulator model of a CCA office building in combination
17 with four different control strategies. A virtual test-bed is developed, con-
18 sisting of two emulated office zones and a temperature modulated Concrete
19 Core activation HVAC system, augmented with persistent faults in temper-
20 ature sensor and hydronic flow rate actuators. Both the fault free (FF)
21 performance and the fault present (FP) performance are investigated and
22 compared through the relevant, control-associated costs using an economic
23 framework. This methodology is able to determine the fault sensitivity of
24 different supervisory control strategies and assists with the selection of the

25 most economical, fault-robust controller for a certain building type. Also,
26 the most critical sensors and actuators are identified.

27 The evaluated faults are shown to be detrimental for the control perfor-
28 mance. The relative economic impact of simultaneous (realistic, randomly
29 distributed and non-correlated) sensor and actuator faults, ranged from +7
30 % to +1000 %. By adhering to an appropriate commissioning frequency,
31 this impact can be reduced. the optimal commissioning period for sensors
32 and actuators was determined to be between 2.8 and 5.0 years (case study,
33 controller and assumption dependent). The lowest financial impact due
34 to degradation faults, for this case study and assumptions, is attained by
35 the closed loop model predictive control (CL-MPC) supervisory algorithm,
36 which incurred only a 15 % relative increase of total present cost, as opposed
37 to increases above +100 % for the other investigated control strategies over
38 the controller lifetime.

39 This study highlights the relevance of taking faults into account when
40 evaluating long term HVAC control performance and quantifies the economic
41 impact of simultaneous persistent sensor and actuator faults on on control
42 performance.

43 *Keywords:* HVAC, MPC, errors, persistent bias, Fault impact, Sensitivity,
44 CCA

45 1. Introduction and background

46 In modern office buildings, the increased uptake of renewable, moderate
47 temperature technologies lead to ever more dynamic interactions between
48 the different HVAC components. While installation and control settings
49 are often kept unchanged over the building lifetime, many building usage
50 parameters, such as number of occupants, preferences and schedules tend to
51 vary drastically over the office building life cycle.

52 The control performance of dynamic systems varies significantly with
53 operating conditions, especially if control settings are not tuned correctly
54 to the system dynamics of the controlled plant. Low-level HVAC systems
55 control is usually of the P(I)D type, which can be notoriously sluggish or
56 oscillatory, if badly tuned (1; 2; 3). Poorly maintained, degraded, and im-
57 properly controlled equipment leads to an estimated 15 % to 30 % of extra
58 energy use in commercial buildings (4). There are many different causes
59 for these degradations: building design and construction is a highly com-
60 petitive, price-driven industry. The application of large safety margins and
61 rules of thumb in HVAC design often lead to equipment over-sizing, causing
62 cycling behaviour of equipment, which result in increased energy use and
63 mechanical wear compared to properly-sized equipment (5).

64 Especially for heavy, concrete core activated buildings, optimal control
65 is challenging (6), since building, installation and user dynamics span a
66 large frequency range ⁶ and since many underlying states are unknown and
67 un-actuated (7).

68 The effect of persistent degradation faults on energy use is highly depen-

⁶from $5.6 * 10^{-3}$ Hz (0.05 h) for low level control and disturbances, up to $3.9 * 10^{-6}$ Hz (72 h) for heavy building element dynamics

69 dent on the type of fault and the fault severity. System performance was
70 reported to be significantly lower when in the presence of faults or when
71 they were induced on purpose. Roth (8) refers to a fault-related "energy
72 waste" in HVAC, lighting and large refrigeration systems between 4 % and
73 20 %. Li (9) investigated the detection and diagnosis of 6 occurring hydronic
74 faults on weather compensated control, optimal start-up and thermal reg-
75 ulation valves on a two-zone school building emulator. In this study, also
76 a questionnaire was sent to 46 maintenance experts of heating systems in
77 France to assess the impact and occurrence of faults in HVAC systems. On
78 average, faults in HVAC installations lead to a 15-40 % increase of yearly
79 energy use (10; 9) compared to the fault free situation. These high percent-
80 ages and wide ranges strengthen our hypothesis that faults should be taken
81 into account in the evaluation of controller performance in office buildings
82 over their lifetime.

83 The combined effects of uncertainty and control settings for model based
84 controllers have been investigated by Privara (11), Maasoumi (12) and others
85 (13; 14; 15). This research has mainly focused on the impact of model error
86 mismatch due to imperfect parameter estimation and unidentified building
87 dynamics. They documented large swings in control performance, often
88 deteriorating, but sometimes a performance improvement, depending on
89 the degree of model mismatch and the reference used. Also, while some
90 controller formulations had negligible sensitivity even to large model mis-
91 matches, others controller algorithms were very sensitive. Castilla (16) made
92 a comparison of thermal comfort predictive control strategies and their pos-
93 sible trade-offs. These observations strengthen our hypothesis that apart
94 from energy use evaluation, also comfort evaluation and supervisory con-
95 troller types should be taken into account when evaluating control perfor-

96 mance in office buildings over their expected lifetime.

97 Only a limited amount of completed research was found in the area of
98 modelling strategies for common HVAC faults. The development of diagnos-
99 tic fault models is severely hampered by the scarcity of measured data on the
100 (in-operation) effects of individual faults on HVAC equipment performance.
101 Several studies exist on FDDe performance evaluation in offices, but these
102 fault models and performance evaluations mainly focus on single HVAC-
103 installations (AHU, chiller, boiler). Haves (17) modelled common chiller
104 faults using a first principle model (white box) and an empirical approach
105 (black box model) based on measurements of known (induced) fault states.
106 Braun (18) made a shortlist, frequency table and analysis tool for chiller re-
107 lated faults. Basarkar (19) used the Energy Management run-time Scripting
108 (EMS) functionality in Energyplus (EP) to model and evaluate the energy
109 impact of several VAV box damper failure. Basarkar (19) implemented 5
110 common AHU faults in Energy Plus using custom EMS schedules. Trcka
111 (20) developed a custom Trnsys type to model common hydronic heating
112 circuit faults. However, faults also occur in building-integrated distribution
113 (e.g. active hydronic controllers) and/or emission systems (e.g. FCU, CCA)
114 and may have a performance impact beyond the system they originate in.
115 In these studies, there was no clear description of what type and severity of
116 persistent faults should be considered when evaluating the economic impact
117 of faults on building-wide HVAC (control) performance in office buildings.

118 The building-wide impact of (white or colored) sensor- and actuator-
119 noise, additive and multiplicative faults on closed loop HVAC control perfor-
120 mance is investigated less often in full building and installation emulations.
121 To the authors knowledge, only Visier (21) investigated faults commonly en-
122 countered in six hydraulic heating systems in medium to large size residential

123 and non-residential multi-story buildings, for space heating as well as for do-
124 mestic hot water heating. A heat generation plant with non-condensing gas
125 boilers, with a design temperature around 90 °C were assumed in this study,
126 including boiler control and sequencing, scheduling of occupancy periods
127 and adaptive control for the temperature setpoint of each secondary loop
128 (RBC) with secondary loop flow control by thermostatic flow-regulation con-
129 trol valves (TRV). An optimum start-stop algorithm for the primary circuit
130 and variable flow temperature control of the temperature difference in the
131 primary loop was assumed. However, this study is not up to par anymore
132 with the current state of technology and state of controllers and this control
133 strategy is not applicable to concrete core conditioned buildings.

134 In order to actively minimize fault impacts, the occurring fault(s) may
135 be detected, diagnosed and overhauled. Then, if economically feasible and
136 technically possible, the faulty equipment can be overhauled or re-calibrated,
137 or the control algorithm may be reconfigured. A lot of research regarding
138 fault impact and fault detectability in HVAC installations has been per-
139 formed already and several FDDe (commercially available) products have
140 been developed by academia and industry. However, the FDDe problem in
141 office buildings is complex, since HVAC systems are large in scale, consist of
142 many interacting subsystems, are building- and equipment-dependent and
143 mostly operate under time-varying boundary conditions. From the reviewed
144 literature and BEMS-market investigation (9; 22; 23), it becomes clear that
145 the uptake of FDDe technology is still minimal in BEMS applications, even
146 in high-end buildings with state of the art control systems. Up to this date,
147 it is not common market practice to perform a manual or continuous, regu-
148 lar (yearly or 5-yearly) commissioning in office buildings in order to detect
149 and rectify erroneous control loops or degraded components.

150 In this paper, the economic impact of persistent faults are investigated
151 for an hydronic HVAC system in a concrete core activated office building.
152 Note that only persistent faults during the operational lifetime of the sen-
153 sor and actuator are investigated, not *component failures* (loss of signal or
154 responsivity). As an office building’s HVAC system is rarely implemented
155 redundantly, when a component failure occurs, it is required to replace this
156 component to continue normal HVAC operation. This is out of scope of this
157 paper. The focus lies on the (frequently occurring) case in which faulty (but
158 not failing) sensors and actuators with persistent faults are continued to be
159 used for HVAC control.

160 The evaluated faults include sensor to actuator faults of different severity
161 and combinations of bias, scaling and white noise perturbation of signals.
162 These fault types commonly occur both on input signals (sensors) and out-
163 put signals (actuators), both in positive and negative sense (increase or
164 decrease of the signal) and at several severity levels, depending on the level
165 of degradation of the HVAC component. Following three generic fault types
166 are investigated:

- 167 • BIAS: Additive input faults. These are frequently occurring with a
168 relatively large impact.
- 169 • SCALE: Multiplicative errors. These have a lower occurrence, with a
170 potentially large impact.
- 171 • NOISE: White noise. These are frequently occurring, with low impact.

172 An emulator model of an HVAC installation, building and user was de-
173 veloped. For maintainability and reliability, most HVAC components in
174 office buildings are typically decoupled into a production section, distribu-

tion section and emission section, each equipped with their proprietary low level controllers. They are controlled by external control signals coming from a supervisory controller, mostly residing in a building energy management system. Four different supervisory controller models were developed. Their performance for several fault combinations was evaluated using the resulting simulated energy cost and discomfort costs over a reference year:

- RBC: a rule based, open loop controller based on a heat curve (HC). The weighted historic daily average ambient air temperature is used to determine a supply setpoint.
- OL-MPC: a open loop model predictive controller, pre-calculated using a state space building model both as control model and emulator model.
- CL-MPC: a moving horizon, closed loop model predictive controller, based on a deterministic state space building model.
- R-MPC: a moving horizon robust model predictive controller based on a stochastic state space building model which takes bounded additive sensor and actuator uncertainty into account.

For this evaluation, the control performance of each simulation variant (in fault free and fault-present conditions) is evaluated using two key performance indicators (KPI): energy cost and discomfort cost. These KPIs are summed over a yearly simulation and normalized. Subsequently, these resulting costs for fault free and fault-present situations are merged (per controller) and evaluated over a 10 year horizon using the economic Present Cost (PC) framework.

199 The main contributions of this paper revolve around the following three
200 research questions:

- 201 • Sensitivity to Faults: Which faults have significant impact on HVAC
202 control KPIs? Is this influence mostly linear, exponential, logarithmic
203 or highly non-linear i.f.o. fault severity? Could this impact be
204 predicted a-priori (for this case study)?
- 205 • Fault Robustness: Are there types of (model-based) controllers with
206 which (a-posteriori) fault impact is minimal for this case study? What
207 type of controller is the most robust for a bounded fault severity (for
208 this case study)? Does the fault impact have an effect on the relative
209 ranking of the compared HVAC controllers for this case?
- 210 • Fault Detectability: Is there an optimal FDDe detection sensitivity,
211 which limits the KPI degradation for one or more controllers to an
212 allowable, low level? What commissioning frequency and cost would
213 be viable for an optimal economically viable FDDe implementation
214 (for this case study)?

215 2. Methodology

216 The approach in this paper is to model an office building with an inte-
217 grated HVAC system, split up in a production, distribution and emission sec-
218 tions, together with model based HVAC controller(s). These are combined
219 and emulated both in FF and fault-present (FP) situations. It would be
220 interesting to validate fault impact, using actual measurement data, should
221 it be available. However, it is theoretically impossible to obtain both re-
222 liable fault-free control performance and fault-present performance at the

223 same time (with same disturbances) from an office building in use. It would
224 be neither comfortable nor energetically acceptable to induce several se-
225 vere HVAC faults, which (may) hamper occupant productivity and comfort.
226 Therefore, the simulation based methodology was used here, with the as-
227 sumption that the emulator behaviour is modelled to sufficient detailed, so
228 it has comparable dynamics to the real reference office building.

229 As building layout, a mid-section of a multi-story office building with a
230 perimeter landscape layout and a central corridor is represented using three
231 thermal zones: a central corridor in the middle and two office zones at either
232 side. Two generic office zones, in the middle of the office building, each with
233 a different orientation (opposite faade) are considered in the emulator, as the
234 impact of faults on individual zones with non-equal disturbances during the
235 reference year (irradiation, wind, occupation) may be not symmetric. Using
236 this multi-zone emulator, the differences and interaction between the zones
237 can be taken into account too, which could not have been evaluated with
238 a one zone model. The used case study building model, HVAC model and
239 controller models are described in detail in appendix A, for reproducibility
240 purposes.

241 In the remainder of this section, the focus is placed on the fault emula-
242 tion, the economic framework, the design of the simulation experiments and
243 weighting (tradeoff) of impact scores.

244 *2.1. Fault models*

245 Persistent faults (bias, multiplicative errors and noise) are introduced on
246 sensors and actuators For the fault evaluations, several sensors and actua-
247 tor models -as described in table 1- are extended with a parametric bias,
248 scale and noise faults on the signals. Note that faults on flow and supply

249 temperature are non-additive in nature and they are highly interactive with
 250 temperature faults, as their combined fault effects are reinforced or partially
 251 negated.

Similar to the methodology applied by Du (24), input and output errors are added to the output signals from the controllers, or added to emulation data, before sending simulated data to the (supervisory or low level) controllers. As a fault model, following generic structure is used:

$$x_{h,i,j} = (1 + m_{h,i,j}) * \bar{x}_h + a_{h,i,j} * n(\mu, \sigma) + b_{h,i,j} \quad (1)$$

252 with $x_{h,i,j}$ the faulty variable value (fault-present), $\bar{x}_h$ the true (fault-free)
 253 variable value, $a_{h,i,j}$ noise amplitude (the fault amplitude added on random
 254 normal distribution), $b_{h,i,j}$ the bias error (additive fault offset), $m_{h,i,j}$ the
 255 scaling error (multiplicative fault offset), $n(\mu, \sigma)$ a normally distributed error
 256 with mean μ and variance σ , h the (faulty) component index (FC), either
 257 $T_{aa} / T_{as,N} / T_{ws,N}$, $Fl_{ws,N} / T_{oz,N} / Fl_{ws,N}$ or $T_{oz,S}$, i is the fault type (FT),
 258 either bias/multiplicative/additive, and j : the fault severity (FS) and sense:
 259 either small/mediocre/large and either increase or decrease.

260 For the univariate and bivariate evaluation of each fault type, a small,
 261 medium or large fault severity was selected depending on sensor and actuator
 262 type, as given in table 2.1. The values for light and mediocre faults are
 263 derived as fractions of the values set for the large fault. These (large) fault
 264 values are also used as a starting point for the fault probability assumptions
 265 for the LHS analysis.

266 For the LHS analysis, a normal distribution is assumed for each fault
 267 type, with a mean μ of 0, and a variance σ^2 of 1/4 (standard deviation σ
 268 1/2). As the assumed standard deviation, half of the large fault severity
 269 was assumed. The corresponding cumulative probability density function

Type of variation	Variant 1	Variant 2	Variant 3	Variant 4
Controller type	RBC	OL-MPC	CL-MPC	R-MPC
Sensors (4)	$T_{aa,N\&S}$	$T_{zo,N\&S}$	-	-
Actuators (5)	$T_{ws,N\&S}$	$F_{ws,N\&S}$	$T_{as,S}$	-
Fault Type (3)	Bias (A)	Scale (Gain M)	Noise (ampl. AN)	-
Fault severity (3)	Large (L)	Mediocre (M)	Small (S)	-
Fault direction (2)	Increase	Decrease	-	-

Table 1: Description of the investigated parameter space for the persistent fault impact analysis. Several linear combinations of these different controllers, components (sensors and actuators), fault types, severities and directions are made. Add = Additive, ampl. = amplitude.

FC	Qty	Add. (B)			Scale (M)			Noise (AN)		
		S	M	L	S	M	L	S	M	L
T-sens.	3	2/3	4/3	2	3.33 %	6.67 %	10 %	0.33	0.67	1
T-act.	1	2/3	4/3	2	3.33 %	6.67 %	10 %	0.33	0.67	1
F-act.	2	4.8	9.6	14.4	3.33 %	6.67 %	10 %	0.48	0.96	1.44

Table 2: Fault severity values used to emulate large faults (L) on different faulty components (FC), for single fault analysis of Temperature (T) and Flow (F) actuators (act.) and sensors (sens.). A small (S) fault is assumed to be at 1/3 of the large (L) value and a mediocre (M) fault severity at 2/3 of the large fault value. Both positive (+) and negative (−) variations are introduced. The large fault parameter values are based on the tabulated process calibration uncertainty in HVAC systems, as reported by Kim (25). Bias and noise are absolute values, while scale is relative %.

shows that with these assumptions (with sufficiently large population), 50.0 % of the random LHS-fault realisations will be below the mild level, 81.8 % below the mediocre fault level and 95.4 % below the large fault level.

2.2. Key performance indicators (KPI)

For each simulation variant (both fault free and fault-present), the control performance is evaluated using following KPIs, summed over a yearly simulation and normalized to the occupied reference office floor area of the emulation model (24 m²):

- The energy cost [€/m²/y] is defined as the sum of yearly heating and cooling energy use of the hydronic and the air-sided system [kWh/m²/y], each multiplied by respective system efficiencies [-] and energy price [€/kWh]. For heating, the energy price (for gas) is fixed at 0.05 €/kWh, and for cooling, the energy price for electricity is fixed at 0.20 €/kWh.
- The discomfort cost [€/m²/y] is defined as the sum of yearly under-heating and over-heating discomfort, averaged over the two office zones (north and south), multiplied by the average cost of discomfort for the building (0.05 €/K h/m²/y).
- The maintenance cost [€/m²/y] is estimated based on the type of HVAC installation type, fault occurrence and overhaul frequency. For a single fault, a fixed maintenance fee of 5/m² is assumed per intervention. For an LHS fault pattern, a maintenance budget of 25/m² is foreseen for detection and replacement of the faulty component(s). This cost is seen as an investment cost and is discounted completely to year zero of the economic evaluation period.

295 The average estimated productivity decrease and estimated average oc-
 296 cupant wage and occupation density are combined to obtain a single weight-
 297 ing parameter that quantifies the economic impact of discomfort. When
 298 assuming a linear productivity decrease of 3 % for a weighted discomfort of
 299 $2Kh$ (26), an area weighted gross personnel wage cost of $6.000 \text{ €/m}^2/\text{y}^7$, and
 300 $1800 [h_{working}/\text{y}]$ working hours per year, the scaling value of this discom-
 301 fort weighting parameter becomes $0.05/Kh/\text{m}^2$. With this discomfort cost
 302 weighting parameter, a simulated or calculated weighted sum of yearly ther-
 303 mal discomfort $[Kh/\text{y}/\text{zone}]$ can be directly converted to a comfort-related
 304 cost. The limit of $100Kh/\text{y}$ acceptable overheating and undercooling, corre-
 305 sponds to a maximal acceptable discomfort cost of $5/\text{m}^2/\text{y}$ one-sided eval-
 306 uation of office buildings (or $10/\text{m}^2/\text{y}$ when evaluating both heating and
 307 cooling).

308 2.3. Unified evaluation criterion

309 For evaluating and comparing costs over multiple years, the present cost
 310 (PC) method is used, where yearly costs (e.g. energy cost, discomfort cost)
 311 are depreciated over the life time horizon of the controller and discounted
 312 to the year 0. In addition to this yearly cost, there are several other related
 313 costs that are case and controller dependent, but only occur once over the
 314 lifetime of the controller, such as replacement costs, investment costs and
 315 (re-)commissioning costs. To take these into account, formula 2.3 is used:

⁷The average annual office personnel cost $[\text{€/y}]$ weighted to floor area (m^2) for office
 buildings is estimated between 2.000 and $12.000 \text{ €/m}^2/\text{y}$, assuming an average occupancy
 of 0.1 person/m^2 and an average gross yearly wage of 20.000 to 120.000 € (27)

$$\begin{aligned}
C_{PC_{y=0},CT} = & w_{PC,C} * C_{C,CT,\star} \\
& + \sum_{y=0}^{t_{eval}=10-1} \frac{C_{E,y,CT,\star} * (1 + i_E)^y}{(1 + i_I)^y} \\
& + \frac{C_{D,y,CT,\star} * (1 + i_W)^y}{(1 + i_I)^y}
\end{aligned}
\tag{2}$$

with C_x the associated costs, which can be either total present cost (PC), capital investment cost (C), energy cost (E) or Discomfort cost (D); CT the supervisory controller type: either RBC, OL-MP, CL-MPC or R-MPC; y the simulated yearly KPI performance; i the yearly inflation rate for energy and wages and $\star$ denoting the corrected value, including effects of commissioning. This equation can be rewritten as a linear combination of three economy-dependent weights, that can be pre-calculated independent of the associated base costs, as shown in equation 3

$$\begin{aligned}
C_{PC,CT} = & w_{PC,investments} * C_{investment,CT} \\
& + w_{PC,e+i} * C_{Energy,y,CT,\star} \\
& + w_{PC,w+i} * C_{Disc,y,CT,\star}
\end{aligned}
\tag{3}$$

with w the fixed weight factors, $e + i$ the effect of energy and inflation, and $w + i$ the factor related to wages and inflation.

The yearly inflation rate i_{infl} assumed in this paper is fixed at 2.2 % (28) based on the 5 years forward 5 years ahead estimates from the European central bank (28). The expected yearly change in energy cost i_{energy} is also fixed at 2.2 %, as the energy cost is a primary driver of the index and

therefore is closely related to the inflation rate. The expected yearly wage cost change i_{wages} at 3.1 % based on figures published by Hay (29).

A sensitivity study on these parameters (between 0 and 4 % for each parameter) shows that the relative tradeoff ratio of energy cost against maintenance and discomfort cost barely changes when inflation rate changes (influence on the ratio over the investigated range stays below 2 %, *ceteris paribus*), but relative shifts of energy cost versus wage depreciation does have a major influence on the cost scaling (-16 % to +20 % change of tradeoff ratio). A steeper energy price increase rate relative to wage increase, decreases the relative cost of discomfort and maintenance, which favours more energy efficient controllers but disfavors regular (more costly) maintenance. On the other hand, a reduction of assumed energy price raise (relative to wage increase) favours regular maintenance and controllers which aim for good comfort.

The controller evaluation horizon $t_{eval,c}$ lifetime is fixed at 10 years. The cost calculation depreciates the related costs to year 0 as presented in equation 2.3. Based on these assumptions, the investment cost weight $w_{PC,investments}$ is 1.00, the energy and inflation related weight $w_{PC,e+i}$ is 10.41 and the wages and inflation related weight $w_{PC,w+i}$ is 10.00.

$$C_{k,mean} = \frac{(w_{FF,k} * C_{k,PC,FF}) + \sum_{FC=1}^{n_{FC}} \sum_{FT=1}^{n_{FT}} \sum_{FS=1}^{n_{FS}} (w_{FP_{FT,FS}} * C_{*,PC,FC,FP_{FT,FS}}^*)}{(w_{FF,k} * n_{FF} + w_{FP_{FT,FS}} * n_{FC} * n_{FT} * n_{FS})} \quad (4)$$

with index k denoting the type of KPI: energy or discomfort cost, index CT denoting the supervisory controller type, index FC the faulty component (FC) type, index FT the fault type and FS the fault severity. Since some large faults, or faults with large comfort impact might be easily detected

354 and overhauled, this cost function is extended, as shown in equation 5 to
 355 place less weight on a detectable fault. In that case, (part of) the yearly cost
 356 corresponding with a single fault is replaced by the sum of the yearly cost
 357 of fault-free performance, and a commissioning fee to detect and replace the
 358 faulty sensor . In this event, an appropriate commissioning weight factor β
 359 and corresponding commissioning cost $C_{comm,h}$ should be chosen for each
 360 faulty component h.

$$\begin{aligned}
 & C_{t,FP,yearly,CT,FC,FT,FS}^* = \\
 & \begin{cases} C_{t,FP,CT,FC,FT,FS} & \text{if } C_{Disc,FP,CT,FC,FT,FS} \leq C_{Disc,limit} \\
 \beta * C_{t,FF,CT} + (1 - \beta) * C_{t,FP,CT,FC,FT,FS} \\
 + 1/2 * w_{PC,w+i} * C_{comm,FC} & \text{if } C_{Disc,CT,FP,FC,FT,FS} > C_{Disc,limit} \end{cases}
 \end{aligned} \tag{5}$$

361 For the LHC sampling tests, the control performance results can be sum-
 362 marized similarly. Also here, when the associated discomfort cost is unlikely
 363 high (above a discomfort detection limit $C_{disc,limit}$, it is assumed that facility
 364 management detects the fault prematurely, and shifts the control towards
 365 fault free (or fault-reduced control) situation again. This will come at a cost
 366 $C_{comm,LHS}$, related to fault detection, and equipment overhaul. Also here
 367 (similar to equation 5) a suitable estimate of commissioning frequency β and
 368 cost per intervention is required. For this case study, the β factor is chosen
 369 to be 50 % (which corresponds to a commissioning frequency once every 5
 370 years), and the added commissioning cost $C_{comm,h}$ is fixed at 5 €/m²/y for
 371 single faults and 25 €/m²/y for LHS faults according to:

$$C_{LHS,CT} = \begin{cases} \sum_{l=1}^{n_{LHS,CT}} (C_{t,FP,l,CT})/n_{LHS} & \text{if } C_{l,disc} \leq C_{disc,limit} \\ \sum_{l=1}^{n_{LHS,CT}} (\beta * C_{t,FF,CT} + C_{comm,LHS} + (1 - \beta) * C_{t,LHS,CT})/n_{LHS} & \text{if } C_{l,disc} > C_{disc,limit} \end{cases} \quad (6)$$

with $C_{t,FF,CT}$ the fault-free performance cost relating t (energy or discomfort) for controller type CT and $C_{t,LHS,l,CT}$ the KPI value relating t (energy or discomfort) corresponding with the LHS-sample with index l , and with l the index for the LHS realization (simulation), For this paper, $n_{LHS,CT}$ was fixed at 20.

2.4. Experiment setup

Using this emulator model and building control models, a large subset of HVAC types, controller models and fault variations were emulated. As simulation settings, the simulation duration was chosen at one year, with a low level control timestep of 12 minutes, and a supervisory control timestep of 1 hr.

For a single fault occurrence in combination with the RBC and OL-MPC, every linear combination (one faulty component and one fault type at a time, 1512 variants) is evaluated. For the other controller variants, this full analysis is not performed, due to the long calculation times for these simulations and due to the similar profiles obtained for RBC and OL-MPC.

For bi-variate fault occurrence (two fault types persisting simultaneously on different sensors or actuators), all combinations of a mild fault and any single other fault severity was evaluated, but only in combination with controller type RBC (2268 combinations).

For a combined fault evaluation, simultaneous stochastic fault occurrences (normally distributed around fault-free condition) on all sensors and actuators are investigated. On this vast search space, a Latin hypercube sampling (LHS) with an assumed normally distributed fault occurrence for each fault severity was performed. For each supervisory controller, 20 cases are simulated.

3. Simulation Results

3.1. Fault free analysis

The developed emulator (described in appendix I) is used to simulate the FF and FP performance of the different case studies and controllers. For each combination of CT and (set of) FT, yearly simulations are executed. An exemplar resulting weekly zone temperature profile in fault-free conditions are shown in figures 1 and 2, for the four controller types, together with their hydronic and aereolic set points and energy use. From these simulation runs, the economical KPIs for yearly energy and yearly discomfort cost $C_{t,FP,CT,FC,FT,FS}$ [€/m²/y] are computed for each evaluated univariate, bivariate or LHS fault combination: One for yearly discomfort cost and one for yearly energy cost.

Fault-free control performance is shown in figures 1 and 2. During spring season (figure 1), the R-MPC and CL-MPC maintain a slightly lower temperature than the other two controllers, but each controller is able to maintain comfortable zone conditions. The RBC has a slightly higher average operative temperature, both because of a higher initial zone temperature and from heating slightly too much. CL-MPC and R-MPC are able to maintain the zone temperature in the thermal comfort band in a more energy-efficient

417 way, by utilizing the air-based installations more, while OL-MPC mostly
 418 provides cooling through the water-based installation. In winter season and
 419 in fault-free conditions (figure 2), the more conservative R-MPC steers the
 420 operative zone temperatures to the center of the comfort band, mostly using
 421 the air sided temperature control, resulting in a heating energy cost simi-
 422 lar to the reference control (RBC), which is designed with a fixed heating
 423 curve air supply temperature. However, the R-MPC uses a quite aggres-
 424 sive changeover strategy. This can be explained as the R-MPC minimizes
 425 the sum of energy use and discomfort attained under worst case additive
 426 uncertainty, while this additive fault is not present here.

427 Comfort and energy performance on a yearly basis can be evaluated
 428 visually based on the yearly temperature duration curves and yearly load
 429 duration curves. These are shown in figures 3 and 4 for all controller types
 430 in FF conditions. From the production load duration curve (figure 4), it
 431 can be seen that both CL-MPC and R-MPC utilize a full load capacity
 432 more frequently than the other controllers, but do not operate as often in
 433 part load. The temperature profiles are comparable, with a slight increase
 434 of under-heating discomfort attained by the R-MPC, and a slight increase
 435 of under-cooling by OL-MPC and (conservative) min-max R-MPC. On the
 436 other hand, in fault-free conditions, the temperature duration and load pro-
 437 files for OL-MPC and RBC are similar, with only some variations within
 438 the thermal comfort band.

439 The weighted (fault-free) PC performance of all controllers are all sum-
 440 marized in table 3. This table shows that under fault-free conditions, the
 441 OL-MPC has the best performance of all evaluated supervisory controllers.
 442 Especially the discomfort cost is minimal for this controller, but also the
 443 energy use cost is relatively low (though a bit higher than the CL-MPC).

Controller type	Present cost	Energy Cost	Discomfort cost	Maint. cost
CT	$C_{PC,CT}$	$C_{E,LHS,CT}^*$	$C_{D,LHS,CT}^*$	$C_{M,FP,y,CT}$
-	$[\text{€}/m^2/10y]$	$[\text{€}/m^2/y]$	$[\text{€}/m^2/y]$	$[\text{€}/m^2/y]$
RBC	60	2.69	3.18	0
OLMPC	52.5	2.45	2.68	0
CLMPC	81	3.41	4.51	0
RMPC	50	3.2	1.73	0

Table 3: Present Cost for each simulated controller in fault-free (FF) conditions

3.2. HVAC Performance under persistent Faults

In the subsequent graphs 5 and 6, the uni-variate and full search space (LHS) fault simulation results are summarized in a scatter plot of HVAC energy cost versus discomfort cost, based on $[Kh/y]$. For each controller, also the fault-free KPI performance and the average PPD [%] in fault-free and fault-present are given in comparison in table 4. Graph 5 and 6 show the impact of a single fault, in combination with the RBC and OL-MPC respectively, as a function of type of fault and ordered by fault severity for each faulty component. On these graphs, it can be seen that single faults have a wide range of impact on energy use and comfort, which both depend on the faulty component and the type of fault. Especially comfort is negatively affected when a single fault occurs. With RBC, the zone temperature sensors $T_{o,N}$ and $T_{o,S}$ are the most critical components (lowest robustness). The sensitivity to T_{ws} and T_{aa} faults is minimal. On the other hand, the OL-MPC is quite sensitive to faults on T_{ws} and T_{aa} , especially with bias errors.

For most univariate faults, the impact on comfort is negatively correlated to the impact on energy use. However, note the scale difference in the graphs:

Simulation runs	WUH	PPD
-	mean, stdev [Kh]	mean, stdev [%]
RBC, FF (1)	79.4, 0	10.76, 0
RBC, LHS (20)	198.2, 675.2	10.76, 2.03
OL-MPC, FF (1)	67.1, 0	8.91, 0
OL-MPC, LHS (20)	273.3, 839.0	8.28, 0.35
CL-MPC, FF (1)	52.6, 0	8.23, 0
CL-MPC, LHS (20)	111.0, 497.3	9.06, 1.66
R-MPC, FF (1)	43.2, 0	7.33, 0
R-MPC, LHS (20)	320.9, 38.5	7.31, 1.05

Table 4: Comparison between average and standard deviation of the thermal comfort performance of several fault scenarios and controller types, expressed in two discomfort performance indices: Weighted undercooling/underheating hours (WUH) and Percentage of people dissatisfied (PPD). For PPD, a clothing factor of 1 *clo* was assumed, with a metabolic rate of 1.2 *met* and a relative air velocity of 1 *m/s*. Note that average increase of yearly averaged PPD of fault-present versus fault-free reference is often small while the incurred discomfort in [Kh] is relatively large. The variance of WUH metric is larger than the variance in PPD. Note that only thermal comfort is evaluated with the WUH methodology, while PPD evaluates hygrothermal comfort. Therefore, the [Kh]-index is a more appropriate and sensitive thermal discomfort KPI for our purpose.

462 the absolute impact of a single fault on cost comfort is typically 10 times
463 higher than the effect on energy use. Therefore, the combined impact of a
464 discomfort cost increase and a (slight) energy cost decrease, typically results
465 in a net cost increase.

466 Graph 7 summarizes the impact of simultaneous (normally distributed)
467 faults on all sensors, on control performance of the four evaluated controllers.
468 The squares and dotted line (bottom side of the graph) depict the theoretical
469 minimum energy use with limited but perfectly controlled HVAC emission
470 capacity, determined using a simple set point controlled low level controller.
471 As most points have shifted to the right on this graph compared to the ref-
472 erence, instead of upwards, it can be concluded that multiple simultaneous
473 (LHS) faults have an especially detrimental impact on discomfort cost (up
474 to +1200 % for the evaluated severities) while they have a much smaller,
475 but non-negligible impact on energy cost (up to +350 % for the evaluated
476 severities). Note that this graph is not scaled for the macro-economic effects
477 over the lifetime of the controller. As the weighting factors for each param-
478 eter is slightly different, a slight tilt in the equi-cost lines will occur, when
479 these effects are taken into account.

480 Following the economic framework and weighting methodology described
481 in the previous chapter, these KPI's are merged, economically weighted
482 and summarized in table 5. The contributing reference cost and simulation
483 output datapoints are presented in table 3.

484 The possibility of resetting the fault impact towards the fault-free per-
485 formance when a high discomfort is detected (e.g. above 100 Kh/y, corre-
486 sponding to 10 €/m²/y), was also taken into account. For the LHS fault de-
487 tection and overhaul, a commissioning cost of 25 €/m²/intervention every
488 two years was assumed (a weighted sum of 20 % of average LHS performance

Controller type	Present cost	Energy cost	Disc. cost	Maint. cost
CT	$C_{PC,CT}$	$C_{E,LHS,CT}^*$	$C_{D,LHS,CT}^*$	$C_{Maint,FP,y,CT}$
-	$[\text{€m}^2/10y]$	$[\text{€}/\text{m}^2/y]$	$[\text{€}/\text{m}^2/y]$	$[\text{€}/\text{m}^2/y]$
RBC	109.7	3.83	6.24	0.63
OLMPC	115.3	3.23	6.72	1.25
CLMPC	89.3	3.79	4.06	0.88
RMPC	110.6	3.16	6.85	0.75

Table 5: Present Cost for each simulated controller under the presence of LHS faults, taking into account commissioning of faulty components in high-discomfort cases at a fixed commissioning frequency (Corrective weight: 20 %, commissioning cost: 25 $\text{€}/\text{m}^2/\text{intervention}$).

and 80 % of the FF performance is used). This corresponds to a bi-yearly overhaul rate. These last two parameters are linked (commissioning cost and overhaul performance), as an increase of the number of interventions will also increase the yearly maintenance cost.

An optimum cost trade-off was determined for each controller as shown visually in figures 9. The results are presented in table 6. This approach, based on formula 6 is broken down into constituents at different values of β for the RBC strategy in figure 8. The energy cost and discomfort decline with increased commissioning frequency β (increased maintenance periodicity), but the associated maintenance costs also rise. Therefore, an optimum commissioning frequency or optimal commissioning time window exists for each controller type.

Finally, figure 10 summarizes all LHS simulation PCs for all controllers in one graph, both for the reference case, the fault present case without commissioning, a case with commissioning at regular, fixed interval and at an optimal maintenance periodicity (see table 6 for more details).

Controller type	Tuned PC	Optimal comm. period	Maint. cost
CT $C_{PC,CT,opt}$	$\beta * 10y$	$C_{Maint,FP,yearly,CT}$	
-	$[\text{€}/m^2/10y]$	$year$	$[\text{€}/m^2/y]$
RBC	107.9	3.85	1
OLMPC	113	4.96	2
CLMPC	79.1	3.47	0.6
RMPC	92.1	2.94	1.5

Table 6: Minimal present cost (PC) for each simulated controller under the presence of LHS faults, with optimized commissioning period (frequency) which minimizes the PC (with corresponding yearly commissioning cost equal to $(25/intervention)\text{€}/m^2/y$).

505 4. Discussion

506 From simulation results, summarized in marginal fault impact graphs
507 (figures 5 and 6) and the economical KPI tables (tables 3, 5 and 6) shown
508 in the previous section, several conclusions can be drawn. In this paper, the
509 focus lies on three research questions related to sensitivity, robustness and
510 detectability, which guide the analysis.

511 4.1. Sensitivity

512 Regarding the fault sensitivity of the different MBC, the primary re-
513 search question was, if it is needed to take the fault impact into account
514 during MBC evaluation? It was expected that RBC would be least robust
515 to faults and would be especially fault-sensitive to temperature sensor and
516 actuator bias faults.

517 The impact of single faults to one controller are mostly linearly corre-
518 lated, as seen in figure 5 and 6, but for some faulty components, there is a
519 quadratic (e.g. zone air temperature sensors), or higher order polynomial
520 (e.g. supply water temperature sensor, flow actuator). Especially bias errors

on zone temperature and ambient temperature faults have a large impact. For noise errors, there is no influence of fault direction, which was expected, as the fault is a stochastic, normally distributed noise with mean 0 was assumed.

The impact of a single fault on energy use and discomfort are mostly negatively correlated, as a fault that causes an increase on one KPI, often reduces another one. However, some faults cause an increase of both KPIs, for example noise errors on a zone temperature sensor (*ToS*). For this case study, the impact on discomfort is a lot larger for most CT and FT, a (large) increase of discomfort cost invariably causes an increase of the PC, regardless of the potential positive (decreasing) effect on energy cost. Therefore, the exact FI is very case/controller dependent and highly sensitive to the assumptions made, which makes this impact is very hard to predict accurately a priori.

Based on the single fault impact results, it can be inferred that there is a large sensitivity to bias faults of the zone temperature sensors. Simultaneous faults, especially increase of HVAC supply flow rate, seem to aggravate these effects.

The absolute fault impact is the largest for the OL-MPC and R-MPC (+67.0 and 52.8 €/m²/*lifetime* respectively) and much smaller for the other two evaluated controllers (+15.1 and +48.7 €/m²/*lifetime* respectively). This is to be explained as the closed loop controllers (CL-MPC and RBC) can make corrective actions when a fault causes discomfort, while the OL-MPC has no means to react to these faults on a supervisory level, but undergoes the associated comfort penalties passively. However, the buffering effect of the heavy capacity building, and the fact that a supply temperature is used as a signal variable and not a heat flux, does negate part of the com-

fort cost at the cost of increased energy usage. Therefore, the energy use of the closed loop controllers increases substantially more in the FP situation than energy use of the OL-MPC (which increases slightly). Moreover, the production capacity is used more often at full load conditions, as seen in figure 1. This corrective action, leads to a reduction of the discomfort impact, but also leads to an increase of the energy cost.

The relative impact of combined faults on KPI's is determined based on LHS and then weighted for economical factors and commissioning as summarized in table 5. Without commissioning, the average combined fault impact is substantial for most controllers. It corresponds to an increase of the PC of 113 % (for RBC), +160 % (for OL-MPC) and even up to 197 % (for R-MBC) compared to FF performance. The CL-MPC is able to provide satisfactory performance despite the presence of faults, even without regular commissioning. Un, it outperforms the other controllers and only has a +17 % increase against reference, fault-free performance. Note however, that a perfect prediction of weather disturbances and occupancy are assumed. This controller is by far the most fault tolerant of the investigated controller types and fault ranges.

4.2. Robustness

The mean impact on energy, comfort and maintenance cost, both in fault free and fault present situation is shown graphically in 10 and summarized in table 5 for each controller and scenario. Figure 7 shows the point cloud of the raw data and the summarized total PC for each controller. It can be seen that the relative robustness is indeed better for CL-MPC and RBC than for R-MPC and OL-MPC, as these point clouds are less spread out, especially in the energy dimension.

When neglecting the comfort related costs, in the presence of persistent faults, the OL-MPC would be the optimal choice, as it has the lowest energy cost (with discomfort infringements) for this case. When only discomfort cost is considered, the R-MPC shows the best performance. However, in the presence of faults and when including both energy use and discomfort cost are weighted with realistic costs, the OL-MPC performance deteriorates drastically with a change of associated PC. At an overhaul reaction rate of 50 % (every five years) and a (high) cost of 25 €/per intervention for this case, the CL-MPC outperforms the other investigated options, with a total PC of 96.2 €/m²/lifetime attributed to the occurring faults, followed by the R-MPC with an PC of 102.8 €/m²/lifetime.

The simulation results show that CL-MPC has the lowest overall fault sensitivity. While the R-MPC does show a significant increase of discomfort cost due to faults, no significant increase in energy use was detected in the fault present case. Therefore, this controller implementation has a good robustness to energy cost. The RBC has a moderate overall fault sensitivity.

When regular commissioning is taken into account, the relative impact of faults is lowered to +80 % (for RBC), +119 % (for OL-MPC) and +106 % (for R-MPC). Again, the CL-MPC outperforms the other controllers under these settings and commissioning interval, with a relative impact on PC limited to +14 %. This wide spread supports our conclusion that fault sensitivity should be taken into account when evaluating controller performance.

4.3. Detectability

A fault detection system (to identify and correct faulty behaviour) and suitable commissioning schedule is critical to obtain a good control performance.

Since the impact of univariate medium and large bias faults on the sensors $T_{oa,S}$ and $T_{oa,N}$ are large for all investigated control algorithms (400 to 800 %), striving towards increased accuracy or bias fault detection on these sensors has a large economic value. Sensor bias reduction can be realized by adding redundancy on the sensor side or by executing regular sensor calibration. Improved sensor precision, which lowers sensor noise, can be obtained by averaging multiple subsequent measurements. Alternatively, user feedback could be taken into account, since when appropriate communication channels are set up, the employees can quickly detect and rapport uncomfortable zones.

With realistic maintenance costs assumptions, the economic benefits generated by a regular overhaul are shown to be maximized (cost minimized) when performed every 3 to 5 years (see table 6), as they lead to minimal PC under the economical assumptions and based on the simulation results in this case study.

With a high commissioning frequency (every 3 years), both RBC and R-MPC perform almost equally well economically in this case study. At a commissioning rate of once per 5 years, the CL-MPC had the lowest PC of all investigated controllers. The total cost, calculated as the (weighted) sum of energy use, discomfort and maintenance costs for this case study, in the presence of persistent HVAC-related faults and with regular commissioning was the lowest (79.1 €/m²/lifetime) for the CL-MPC, as seen in table 6.

5. Conclusion

This paper illustrates a economical performance evaluation methodology to examine the performance of HVAC-controllers under the influence of

625 persistent degradation faults, in contrast to the often superior fault-free per-
626 formance. This is demonstrated using an emulated case study of a thermally
627 heavy office building equipped with concrete core activation and controlled
628 by one of four different supervisory control algorithms.

629 The impact of single degradation faults on temperature and flow sensors
630 and actuators is found to be non-negligible and non-linear. Especially bias
631 errors on the zone temperature sensors have a large impact on supervisory
632 control comfort performance. Also faults (bias and noise) present on the
633 water supply temperature control temperature signal severely deteriorate
634 the control performance.

635 The combined impact of simultaneous faults varies widely for the dif-
636 ferent controller types and fault combination instances (-14 % to +1100 %
637 against the reference for the evaluated controller). The resulting average
638 present costs for different supervisory controllers under the influence of si-
639 multaneous, stochastic distributed faults, are consistently higher than their
640 fault free reference performance (+17 % to +200 %).

641 A large variation in controller robustness against persistent HVAC faults
642 was observed. Fault sensitivity caused a change in the relative economic or-
643 der of the supervisory controllers for this case study. While in the fault free
644 situation, the R-MPC was superior and CL-MPC was the least favourable,
645 the CL-MPC and RBC proved to be economically superior when LHS-faults
646 were considered and frequent commissioning was performed. However, the
647 R-MPC excelled at low (or no) commissioning rates. The OL-MPC proved
648 to be very sensitive to common HVAC-faults. For this case and fault as-
649 sumptions, the CL-MPC was the most robust controller. With optimal
650 commissioning frequencies, a relative increase between +10 % and +198 %
651 was observed in total associated present costs.

Commissioning (investments in recalibration and tuning of smart/accurate sensors) is shown to be critical and profitable, as it can reduce the control related costs significantly by overhauling faulty equipment and thereby resetting the control performance to the reference performance. The optimal commissioning frequency for faulty control-related equipment is calculated. It ranges between 3 to 5 years for most controllers. However, this economical commissioning frequency for multi-sensor overhaul is very dependent on the emulated case and on economic and controller parameters.

As these conclusions are only supported by an emulation study for this type of building (Heavy building with CCA) and under fixed assumptions, following topics are recommended for further research: Extending this methodology to other types of buildings (e.g. lower thermal mass or different insulation thickness), other types of HVAC systems (e.g. fan coil units, all air systems, etc) and broader fault types (e.g. coloured noise).

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6. Nomenclature

Following abbreviations have been used in this manuscript:

Acronym	Description
<i>add:</i>	Additive (or offset) fault
<i>AHU:</i>	Air handling unit
<i>AN:</i>	Amplitude of normally distributed noise

<i>B</i> :	Bias, see add
<i>BEMS</i> :	Building energy management system
<i>BAS</i> :	Building automation system
<i>CAV</i> :	Constant air volume (ventilation)
<i>CCA</i> :	Concrete core activation
<i>CLC</i> :	Control life cycle (evaluation period)
<i>CL – MPC</i> :	Closed loop MPC
<i>CT</i> :	Controller type
<i>EM(C)S</i> :	Energy management and control system
<i>ESCO</i> :	Energy servicing company
<i>FC</i> :	Faulty component
<i>FDDe</i> :	Fault detection, diagnosis and evaluation
<i>FF</i> :	Fault free
<i>FI</i> :	Fault impact
<i>FP</i> :	Fault present (situation)
<i>rFP</i> :	Random fault propagation

672 Following symbols have been used in this manuscript:

673

Symbol	Description
<i>C</i>	Financial impact (Cost) [€or €/m ² /y]
<i>T_{aa}</i>	Ambient air temperature [°C]
<i>T_{as}</i>	Supply air temperature [°C]
<i>T_{ws}</i>	Supply water temperature [°C]

Toz	Operative zone temperature [$^{\circ}C$]
F/Fl	Flow rate [kg/h]
N/S	(subscript) Reference to the North or South zone
PC	(subscript) Reference to Present cost, discounted to reference year 0
h	(subscript) Faulty component (FC) index
i	(subscript) Fault type (FT) index
j	(subscript) Fault severity (FS) index
μ	Mean
σ^2	Variance
AN	Amplitude of noise error
A	Offset of bias error
M	Gain of scale error
S	Small FS
M	Mediocre FS
L	Large FS
$E/D/M$	(subscript) Reference to either Energy, Discomfort or Maintenance
y	(subscript) year
CT	(subscript) controller type
i	Inflation rate
$E/W/I$	(subscript) referring to energy cost, wage indexation and price inflation
w	Weight parameter
FF	(subscript) Fault Free
FP	(subscript) Fault present
n	Quantity of evaluated fault realisations
t	Index of multivariate fault realisation
β	Commissioning frequency

$T_{vs/r}$	Air supply or retour temperature [$^{\circ}C$]
T_c	Concrete Core temperature [$^{\circ}C$]
T_s	Surface temperature [$^{\circ}C$]
T_{ia}	Indoor air temperature [$^{\circ}C$]
T_{wr}	Water retour temperature [$^{\circ}C$]
m_w	Water supply mass flow rate [kg/h]
m_{w2}	Bypass flow rate [kg/h]
$m_{vs/rs}$	Air supply mass flow rate [kg/h]
$T_{h/c,prod}$	Plant water supply temperature production for heating and cooling [$^{\circ}C$]

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776 **8. Appendix: Case study description**

777 *8.1. Office building and HVAC emulator models*

778 Several distinct software tools are available to simulate HVAC, faults
779 and model based control. However, software tools that can simulate the
780 combination of detailed HVAC behaviour, fault effects and model predictive
781 control in detail, are more scarce. Suitable HVAC emulation packages ca-
782 pable of the level of HVAC detail investigated in this paper, include (aside
783 from Trnsys): E+, HVACsim, EES, BLAST, DOE2 and Modelica. Faulty
784 signals can be modeled in E+, HVACsim, EES and Modelica. MPC control
785 interfaces with emulation software can be implemented by coupling solvers
786 (e.g. CPLEX, Gurobi) through middleware software (e.g. Python, Matlab,
787 BCVTB).

788 In this paper, the investigated cases and faults are modelled using Trnsys
789 (30), while the HVAC-control is implemented in Matlab (31). Thus a Trnsys-
790 Matlab coupling was required. For this purpose, Trnsys type 155 was used.
791 As an exercise, the possibilities of applying supervisory MPC-control to a
792 E+-emulation have been investigated and implemented in the framework of
793 a master thesis (32), using E+ as an emulator with CPLEX as solver, coupled
794 through middle-ware BCVTB and Matlab.

795 A building construction with high thermal inertia and with thick ther-
796 mally activated building system (TABS) consisting of concrete construction
797 elements (concrete core activation, CCA) are assumed here. The used ma-
798 terial properties are shown in table 10.

799 A schematic representation of the HVAC system is shown in figure 11.

800 For baseload cooling and heating, concrete core activation (CCA) tubes
801 are included (symmetrically) in the floor and ceiling sections of this office

Property	Value	Units
Office section width	3.00	m
Office section depth	4.00	m
Floor to floor height	2.9	m
Floor to plenum height	2.4	m
Glass to wall ratio	50	%
Orientation	N-S and E-W	-

Table 9: Emulated building layout

Component	adjoining:	Thickness	Area	Thermal cond. U	Accessible Capacity
Units	-	[m]	[m ²]	[W/m ² /K]	[kJ/K]
External wall	ambient	-	8.64	0.412	3594
Internal wall	Corridor	-	7.2	0.790	69
Internal wall	office	-	11.6	Adiabatic	Adiabatic
Floor	lower floor	-	12	Adiabatic	6873
Ceiling	upper floor	-	12	Adiabatic	6873
Window	office	-	4.32	1.09 (g: 0.39)	-

Table 10: Building layer build-up

Building mass	Heavy
Cooling production system	idealized chiller
Production Cooling capacity	100W/m ²
Cooling emission system	CCA
Heating production system	idealized boiler
Production Heating capacity	105W/m ²
Heat emission system	CCA
Ventilation	CAV
Climate	TMY2 Uccle, Belgium

Table 11: HVAC sizing and emulator limitations

802 building. These are modelled using the EMPA model (7) embedded in an
803 active building layer, with a fixed flow rate of 14 kg/h/m^2 office area (or 12
804 kg/h/m^2 gross floor area) during operation. The specified tube diameter is
805 0.02 m, with a wall thickness of 0.002 m and a pipe spacing (centre to centre)
806 of 0.15 m. The assumed pipe wall conductivity is 1.26 kJ/h/m/k . The pipes
807 are embedded in the centre of a 20 cm concrete slab, with a 0.075 m screed
808 layer, an air layer (raised computer floor) and 0.04m thick floor-tiles on top
809 of it. The ceiling is covered with a 0.01 cm plaster layer.

810 The water distribution system consists out of two supply collectors (a
811 hot water and cold water collector) and several three way valves, allowing
812 each zone to be independently cooled or heated and have a separate, unique
813 supply setpoint and flow rate. The water supply setpoint for each zones is
814 set every hour, by the supervisory controller. Furthermore, each supervisory
815 control strategy has the ability to override the flow rate towards the HVAC
816 emitters for each zone separately.

817 The installed hot and cold water production capacity for this water based
818 heating and cooling emission system are provided by a central boiler and
819 a central chiller. These are selected with a maximal production capacity
820 of respectively 100 W/m^2 for heating and 105 W/m^2 for cooling. These
821 figures are based on a steady heat load calculation of the building at $-8 \text{ }^\circ\text{C}$
822 for heating and $30 \text{ }^\circ\text{C}$ for cooling, with an additional start-up margin of 200
823 %.

824 While the efficiency of a real HVAC production system is typically not
825 constant, but dependent on boundary conditions and installation, in this
826 study this conservative assumption is made to eliminate differences in con-
827 trol performance between different operational strategies which may exploit
828 production efficiency information. Therefore, it allows us to pinpoint solely

829 the fault impacts due to changes in emission-, control- and distribution ef-
830 ficiencies. A fixed production conversion efficiency (independent of supply
831 temperature or part load ratio) is modelled with a seasonal efficiency ra-
832 tio for heating (sCOP) of 0.9 for heating, and seasonal efficiency ratio for
833 cooling (sEER) equal to 2.5.

834 As ventilation system, a constant air volume (CAV) ventilation system
835 is modelled, with scheduled, fixed supply air flow rates of 43.2 kg/h/m^2 .
836 In the modelled AHU, a thermal wheel with a sensible efficiency of 80 %,
837 a heating coil and a cooling coil are present. No humidification or active
838 dehumidification is performed.

839 Humidity levels of zone air and supply air are not actively controlled or
840 verified in this emulator. Modelling realistic humidity dynamics in detail
841 in the emulator model would require a full hydrothermal model based on a
842 buffer storage model, requiring additional (unavailable) information on the
843 hygrothermodynamics of building materials and furniture in the room to deter-
844 mine realistic parameter values for e.g. gradients of sorption and moisture
845 exchange coefficients. This is out of scope of this study as the focus is on
846 thermal comfort.

847 Some humidity dynamics are however taken into account in the current
848 model (in a simplified manner). A simple capacitance humidity model is
849 used, with a humidity capacitance ratio of 1 for both zones. Also, some
850 (indirect) dehumidification of the ventilation air is performed. A cooling coil
851 is modelled in the AHU, which cools down ambient air to a target supply
852 temperature setpoint following a heat curve. The cooling coil outputs fresh
853 air with a maximal wet bulb temperature of 19-24 °C.

854 Outside of scheduled occupancy, zone air is recirculated and during occu-
855 pancy, 100 % fresh air is supplied, pretreated by the thermal wheel, cooling

856 coil and heating coil, to the desired air supply setpoint T_{sa} .

857 Infiltration is modelled to be 0.05 ACH when the ventilation system is
858 active, 0.2 ACH per hour when ventilation system is off.

859 The air supply setpoint can be set independently for both zones. The
860 RBC provides preheated and precooled fresh air at a supply air setpoint for
861 both zones of 24 °C during winter, and 19 °C during summer conditions, with
862 a changeover condition determined based on the mean outside temperature
863 (15 °C). The other control algorithms can vary the supply temperature
864 between 15 and 30 °C.

865 For occupancy and internal gains, a standardized ASHRAE occupancy
866 time schedule with 1 occupant per 10 m^2 of office space is modeled, between
867 8 AM and 12 AM and 1PM to 6 PM during week days, to resemble a
868 characteristic landscape office occupancy. Corresponding internal sensible
869 heat gains of 75 $W/person$ and 55 $W/person$ latent heat gains are assumed,
870 for seated occupants doing light work. The sensible heat gains are split into
871 convective gains (42 %) and radiative heat gains (58 %).

872 As weather disturbance, the TMY2 weather file for Uccle (Belgium) has
873 been applied to the building. A solar shading system with hysteresis is
874 programmed for the south side, triggered based on two threshold levels of
875 incident solar irradiation on that facade.

876 For comfort evaluations, a target comfort band with a width of 4 °C is
877 used, typically between 20 and 24 °C, but this band is adjusted upwards
878 or downwards slightly at extreme mean outdoor temperatures, based on
879 the adaptive comfort theory. The HVAC emission systems have a target
880 operative air setpoint equal to these boundaries, with an offset of 0.5 °C
881 towards the middle to allow hunting without causing thermal discomfort.

882 This two-zone-office-CCA emulator model was designed from bottom up,

883 using a white box methodology (based on building material properties and
884 good practices). Therefore, no exact one-to-one mapping can be made to a
885 specific existing building.

886 Researchers Maarten Sourbron and Wout Parys have successfully verified
887 the white box parameters of this concrete core conditioned office building
888 emulator; based on measured indoor temperatures and HVAC temperatures
889 in an office building in Belgium, Hasselt, both in open loop operation with
890 response to step inputs and in closed loop operation with a rule based con-
891 troller and also with an MPC implementation. They verified cool-down and
892 heat-up temperature dynamics of measurements and simulation output un-
893 der the influence of different disturbances. The model and procedure are
894 described in detail in their Phd theses (?) and (33) (appendix A).

895 8.2. Supervisory HVAC-Controller implementations

896 Four model based controller types are developed, a RBC, OL-MPC, CL-
897 MPC and R-MPC. In following section, the used control algorithms and
898 control implementation are described for each controller.

899 8.2.1. RBC

900 As a reference supervisory controller, a rule based heating and cooling
901 curve (outdoor temperature reset) controller (RBC) is used. This controller
902 takes the historic (multi-day weighted) outdoor air temperature as an input
903 and calculates appropriate (concrete core actiation and ventilation) supply
904 temperatures based on the heat curve equations 7, with $T_{s,w/a}$ the supply
905 temperature of water or air respectively, T_{aa} the historically weighted ambi-
906 ent air temperature $T_{s,w/a,max}$ and $T_{s,w/a,max}$ the supply temperature limits
907 defined by the facility manager, based on equipment safety and efficiency,

908 T_{ref} the reference temperature; heat curve parameters A (the reference sup-
 909 ply temperature), B (the heat curve slope, depicting the ambient air de-
 910 pendency of the supply temperature) and C (the non-linearity temperature
 911 dependence of emitter and distribution an installation) and with $I_{setback}$ and
 912 I_{boost} time-dependent binary variables which indicate the activation of boost
 913 or night setback mode:

$$\begin{aligned}
 T_{s,w/a} = \min(T_{s,w/a,max}, \max(T_{s,w/a,min}, \\
 + B * (T_{ref} - T_{aa})^C + T_{Boost} * I_{boost} - T_{setback} * I_{setback}))
 \end{aligned}
 \tag{7}$$

914 To find a near-optimally tuned RBC parameter values for parameters
 915 A , B , T_{ref} for each circuit (w: water, a: air) for the fault-free case, a latin
 916 hypercube sampling was performed with 1000 year-simulations with varying
 917 parameter values. One heat curve was used for both zones. The parameters
 918 which lead to the lowest total energy and discomfort cost (with a weight-
 919 ing factor of 0.5) in the fault-free condition using the (simulated) dynamic
 920 response of the emulated building to ambient temperature over a reference
 921 year, are retained. The chosen RBC parameters are given in table 12. The
 922 C -parameter was fixed at a value of 1. The boost term (increased water
 923 supply temperature on Monday morning) and a weekend setback (widened
 924 set-point range) were found not to be required (non-optimal) for this case.

925 8.2.2. MPCs

926 The open loop MPC (OL-MPC) and closed loop MPC (CL-MPC) re-
 927 quire an analytic dynamic system model of the emulator to minimise a cost
 928 function. Either a white box model, black box model or grey box model
 929 can be used for this purpose. In this case, a black box state space model is

Parameter	value
$A_{s,w,c}$	27.9
$A_{s,w,h}$	34.7
$A_{s,a,c}$	15
$A_{s,a,h}$	13
$B_{s,w,h}$	-0.22
$B_{s,w,c}$	-0.16
$B_{s,a,h}$	1
$B_{s,a,c}$	1
C	1
$T_{ref,summer}$	15
$T_{ref,winter}$	13
Boostw,h	0
Setbackw,h	0
$T_{s,w,min}$	15
$T_{s,w,max}$	45
$T_{s,a,min}$	18 (15 for MPC)
$T_{s,a,max}$	20 (35 for MPC)

Table 12: Near-optimal heat curve parameters for RBC control and supply temperature limits used for RBC and MPC control simulation. .

constructed. The identification process is executed in two stages:

First, a pseudo-random-multisine-excitation is applied to the main HVAC-controller inputs and disturbances: water supply temperature $T_{s,w}$, air supply temperature $T_{s,a}$, ambient air temperature T_{aa} , internal gains Q_{int} , irradiation Q_{irr} on one zone (S zone) of the Trnsys emulator (for each of the three building/HVAC cases). The response of following outputs is recorded: indoor air temperature $T_{z,a}$, return water temperature T_{rw} and concrete core temperature T_{cc} . This identification data set is then split in an identification and cross-validation set, with the ratio of samples 10:1. Based on these data sets, a 4-state state space model is identified using the Matlab ident-toolbox . As identification settings, the N4SID-identification method is selected, with a focus on simulation and with a delay of 1 time step (12 minutes) for the inputs water supply temperature $T_{s,w}$ and air supply temperature $T_{s,a}$.

The second zone (N zone) is assumed to have the same response to the input variables, as the building construction and HVAC system is identical. Therefore, the same model is used to control the north and the south zone in the model based controller, both during summer and winter.

As a cost function, a linear cost function (equation 8) is used, consisting of the weighted sum of discomfort cost (underheating and undercooling) and energy cost (water climatization and ventilation), using the parameter values given table 12. Hard constraints are applied to limit the supply temperatures and production heat fluxes. Slack variables are introduced and paired with the operative zone temperature to determine the level of thermal discomfort.

The problem structure, constraints and cost function are expressed using the Yalmip toolbox (34). As a solver, Gurobi (35) was used to solve all

linear, time invariant MPC problems. This cost-function is minimised over the prediction horizon by the MPC controllers for each zone separately. From the optimal result, the requested HVAC temperature setpoints for the production side and zone temperature control valves are obtained.

$$\min J_{z,t} = (W) * (\overline{C_{w,t}} + \overline{C_{a,t}}) + (1 - W) * \overline{C_{d,t}} \quad (8)$$

$$s.t. T_{w/a,min} < T_{s,w/a,t} < T_{w/a,max} \quad (9)$$

$$P_{w/a,min} < P_{s,w/a,t} < P_{w/a,max} \quad (10)$$

$$C_{d,t} = \max(\|T_{comf,min} - T_{a,z,t}\|, \dots \quad (11)$$

$$\|T_{comf,max} - T_{a,z,t}\|, 0) * t * C_{disc} \quad (12)$$

$$C_{w/a,t} = (T_{s,w/a} - T_{r,w/a}) * c_{p,w/a} * t * C_{E,w/a} \quad (13)$$

For the OL-MPC, for each zone an (open loop) optimization problem with an horizon of one year is defined and pre-calculated. The control actions are then applied to the building, with only low feedback control level-adjustments.

For the CL-MPC supervisory controller, a similar approach is used, but with a recurring estimation, and a prediction horizon of only 48 hours for each optimization. State estimation is performed using historic measurements and inputs over a backward horizon of 24 hours. At every control time-step, only calculated control inputs of the control horizon (6 hours) are applied. The choice of a prediction horizon of 48 hours is supported by the dominant frequencies in the building, identified using a step response. The control horizon of 6 hours is chosen to speed up the simulations, compared to a control horizon of 1 hour. The same constraints, quadratic cost function and weights are used for this closed loop controller and for the open loop

975 controller. Due to different horizon length, state estimation and model mis-
976 match, however, this results in a slightly different yearly trade-off between
977 energy cost and discomfort cost compared to the open loop performance.

978 For the R-MPC supervisory controller, the same model structure and
979 horizons are used as for the CL-MPC (the sum of energy use and discomfort
980 is minimized), but bounded additive uncertainty on the input and output
981 are assumed on all faulty signals (sensors and actuators), equal to the light
982 additive fault severity level. A min-max MPC scheme is used, where both
983 the discomfort and energy use in the worst case for every timestep (max), are
984 minimized (min) over the whole prediction horizon. As the building model
985 has positive state-space matrices and the control inputs are all positive (tem-
986 peratures and heat fluxes), this min-max MPC can be implemented using
987 an envelope method with the extreme values of the uncertain parameters.
988 This way, a stochastic R-MPC problem is simplified to a non-stochastic, lin-
989 ear MPC problem, which still takes into account the (worse case) additive
990 uncertainty.

991 8.2.3. Controller implementation

992 For the RBC reference controller and the OL-MPC controller, calculated
993 supply temperatures are applied to the emulator in a feed forward manner
994 without any direct feedback from the HVAC system or zone temperature.

995 On the other hand, both the CL-MPC and the R-MPC follow the reced-
996 ing horizon control principle, with historic output and input feedback. A
997 receding horizon of 6 h is used, with a control timestep of 1 h. Every 6 h, the
998 controller output is recalculated based on latest outputs from the building
999 and the first part (6 hs) of the calculated control output is applied to the
1000 building. No prediction errors are introduced to the MPC controllers: Over

1001 the MPC model prediction horizon, the future solar irradiation, ambient
1002 temperature and occupancy patterns are assumed to be predicted perfectly,
1003 even if a sensor fault is present. No Kalman filtering is applied, but state
1004 estimation is performed based on the measured historic outputs and historic
1005 control inputs.

1006 8.2.4. *Competing control objectives*

1007 Indoor air acclimatization settings mainly depend on the chosen trade-
1008 off between discomfort cost and HVAC running costs. The HVAC running
1009 cost contains mainly energy cost, but might include maintenance cost and
1010 commissioning costs. Also, (one time) case-study- or controller-dependent
1011 investment costs may be included in the comparisons.

1012 For RBC, the weights of this trade-off cannot be defined explicitly within
1013 the control model, but the resulting trade-off can be shifted through non-
1014 trivial adjustment of the RBC parameters. In this emulation case, the heat
1015 curve reference temperature A and heat curve slope B are varied to evaluate
1016 alternative reachable trade-off points for the reference controller in fault-free
1017 conditions. The most optimal (lowest energy and discomfort cost) combi-
1018 nation of multiple random heat curves runs are (assumed) to be on the
1019 Pareto-front reachable by this controller. Especially the heat curve slope B
1020 of the heating curve has a highly (non)-linear influence on yearly energy use
1021 and discomfort (36).

1022 For MPC (OL-MPC, CL-MPC and R-MPC), a trade-off parameter can
1023 be put explicitly in the cost function over the control horizon, but when
1024 evaluated on yearly bases, the resulting KPI trade-off will not exactly equal
1025 this preset value, as it also depends on the model mismatch, prediction mis-
1026 match, equipment sizing and the persistent faults present in the building.

1027 If the weight α placed on energy cost is 1, only the energy cost will be
1028 minimized by the control algorithm, resulting in a temperature profile com-
1029 parable to a free running system (no energy use). If the weight placed on
1030 energy use α is 0, this corresponds to minimizing the cost related to dis-
1031 comfort, meaning the controller aims for a perfect comfort control, at any
1032 (potentially very high) HVAC-related energy cost.

1033 In these simulations, the OL-MPC and R-MPC trade-off weight α are
1034 chosen (a-posteriori) to be 0.5, while the CL-MPC weight is empirically fixed
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Figure 1: Simulated HVAC performance over one spring week, for four different controller types, in a fault free (FF) situation. In the top sub-figure, the bottom (black) line depicts the ambient temperature, the straight lines depict the comfort band and the four other lines show the operational zone temperatures achieved by different control strategies. Pane 2 and 3 contain the water and air supply temperature set by the different control strategies respectively. Pane 4 contains the resulting weekly energy usage.

Figure 2: Simulated HVAC performance over one winter week, for four different controller types, in a fault free (FF) situation. In the top sub-figure, the bottom (black) line depicts the ambient temperature, the straight lines depict the comfort band and the four other lines show the operational zone temperatures achieved by different control strategies. Pane 2 and 3 contain the water and air supply temperature set by the different control strategies respectively. Pane 4 contains the resulting weekly energy usage.

Figure 3: Simulated operative zone temperature duration curve for different CT with chosen weights, for the South zone of the emulated H CCA building case, in a FF situation, during office hours. .

Figure 4: Production load duration curve of the heat and cold production for different controller types with fixed weights, in fault-free conditions, both for heating (top graph) and cooling (bottom graph).

Figure 5: The absolute impact of single fault occurrence on energy cost [$\text{€}/\text{y}$] (top) and discomfort (bottom) cost [$\text{€}/\text{y}$] as a function of type of fault (FT), grouped by sensor component controlled by a Rule Based Controller (RBC).

Figure 6: The absolute impact of single fault occurrence on energy cost [$\text{€}/\text{y}$] (top) and discomfort (bottom) cost [$\text{€}/\text{y}$] as a function of type of fault (FT), grouped by sensor component controlled by an open loop model predictive controller (OL-MPC).

Figure 7: The impact of combined (LHS) fault occurrence on energy use and discomfort, for each of the four controller types. The reference (fault-free) performances (one point per controller) are annotated with diamonds. The weighted mean values, taking into account commissioning when low comfort situations occur, are depicted by triangles. .

Figure 8: Total cost associated costs in function of maintenance periodicity ($\beta \cdot 10$), together with the constituents energy cost, discomfort cost and maintenance cost. .

Figure 9: Total cost associated costs for the four evaluated controller strategies in function of maintenance periodicity ($\beta \cdot 10$). The differences occur due to differences in reference cost, fault impact and high discomfort occurrence.

Figure 10: Overview of the three PC-constituents energy cost (bottom, blue bar), discomfort cost (middle, orange bar) and maintenance cost (top, grey bar) for each controller, in fault free (FF) conditions, under the presence of faults (FP) without commissioning, with regular commissioning (CCx) and with optimal commissioning rate. .

Figure 12: Simulated energy cost and discomfort cost for different weighting parameter values α while applying the OL-MPC controller on the controller model itself. The best economical trade-off is reached at an α value of 0.5 This parameters was used for the tuned OL-MPC. Operation in the area beyond $[10/\text{m}^2/\text{y}]$ discomfort (on the right of the dashed line, marked in red) are typically considered unacceptable. .