# Design of an Energy Management System for buildings: a bottom up approach

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## 1 Introduction

## 2 Problem statement

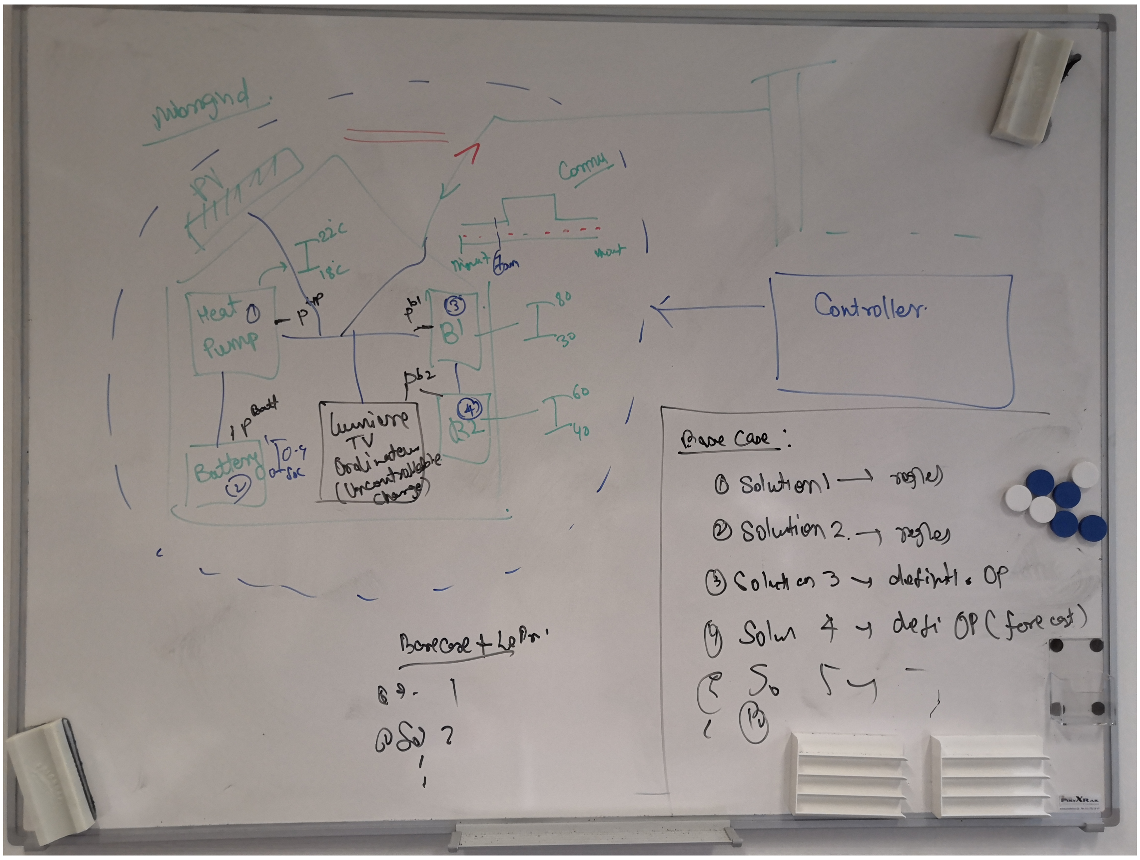


Figure 1: Microgrid sketch (to be changed)

A bottom up approach is taken. A baseline scenario is first proposed and its limitations are studied. Progressively, those limitations are tackled by adding features and complexity to the system, with the unique goal of reducing energy costs. Each of the added features are discussed and their downsides are pointed.

# 3 Scenario 1

The first scenario describes the baseline case of a generic household. In order to produce locally and reduce its electricity bill, a PV system has been incorporated to the building. Now that it can also generate power and not only consume it as a load, the building can be seen as a grid-connected microgrid. In fact, the building can inject excess PV power into the grid via a single two-ways connection. Just as before the PV installation, the household can also consume from the grid whenever PV power is not enough to supply its different loads.

However, grid's electricity comes at a higher price. The feed-in tariff that the household gets for injecting power back to the grid is considerably lower than the cost of consuming electricity from such an unrestricted and reliable source. It is therefore the purpose of an Energy Management System (EMS) to maximise the self-consumption of PV power.

For that, the EMS has the ability to exploit the flexibility of the building. For instance, two electric boilers (B1 and B2) bring thermal storage capabilities to the household. An intelligent EMS would allow to operate those thermo-electric units under certain coordination to actively respond to the microgrid power fluctuations.

In this first scenario, the EMS objective is simply to take advantage of the flexibility of the two boilers. To ensure a certain hot-water supply, B1 and B2 should ideally be operated within min/max limits. Those two temperature ranges are the only degree of freedom for the EMS to operate. In contrast to the supply side which is non-controllable, the demand side can be controlled with the goal of matching PV production.

In a different category than boilers, the remaining household loads are non-controllable and represent another source of uncertainty. Those include lights, TV, washing machine and all human-switched appliances in general.

## 3.1 EMS Components and models

Regarding the EMS implementation, several features are needed. The physical quantities such as boiler temperatures and power consumed by the loads (boilers and non-controllable) need to be communicated to the controller, and same goes for PV generated power. It is assumed that the different loads are self-conscious about their state. For instance, boilers are equipped with temperature sensors. A power sensor is also able to measure the household power consumption (ignoring boilers, that have their own power sensors). Finally, the PV converter is aware of its power. All in all, in the first scenario, the EMS needs 4 measurement inputs.

A communication layer is in charge of broadcasting sensors data to the centralized controller. This one processes such inputs and computes an adequate control action for each of the controllable units. The output is communicated back to the loads, where the actuator ensures that the controller orders are executed.

In order to actively control boilers 1 and 2, a model of such thermal loads has to be incorporated. To avoid over complicating Scenario 1 and letting it as wide as possible, a very simplistic, linearly approximated model is used. The water's thermal capacity $C_w$ describes its ability (and the boiler's) to accumulate heat. Ignoring factors such as heat loss, hot-water consumption and electrical system efficiency, the temperature evolution in the boiler is given by the difference Equation 1.

$$p_b^{elec} = C_w \frac{dT_w}{\Delta t} \tag{1}$$

It is important to precise that the microgrid automatically balances power supply and demand. Under such assumption, any PV power not consumed by the building is absorbed by the grid without the necessity of any control action on the part of the EMS. Similarly, any power demand from loads that cannot be supplied by the PV system is supplied by the grid.

## 3.2 Notations

Control variables are named $u$, whereas measurement variables are named $p$ for load's power or $x$ for load's state. Capital letters designate constant parameters. Indexes refer to specific energy systems. Time value of the variables is be noted with $[h]$, where $h$ designates the current discrete time period of length $\Delta t$, and goes from 0 to $H$. Regarding sign convention, a positive power refers to power that is injected into the microgrid, for instance by the PV system. A negative power is one that is absorbed by loads. Finally, underline ($\underline{\bullet}$) and overline ($\overline{\bullet}$) designate minimum and maximum values respectively and are subjected to the same sign convention.

**PV system**

$p_{PV}$: PV power (kW) ($\geq 0$)

**Non-controllable loads**

$p_{nc}$: power demanded by non-controllable loads (kW) ($\leq 0$)

**Electric boilers**

$u_{B,k}$: target power of boiler $k$ (kW) ($\leq 0$)
$p_{B,k}$: actual power of boiler $k$ (kW) ($\leq 0$)
$\overline{P}_{B,k}$: Max. power of boiler $k$ (kW) ($\leq 0$)
$[\underline{T}_{B,k}; \overline{T}_{B,k}]$: lower and uppers limits on boiler's $k$ hot-water temperature.
$T_{B,k}$: actual temperature of boiler $k$ (°C)

Vectors $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h]$ and $\hat{\boldsymbol{u}}_{\boldsymbol{B}}$ regroup information of both boilers.

## 3.3 Control algorithm

The controller is configured by establishing rules determined by all possible system operating scenarios. It receives measurements of all system states and uses those to take myopic decisions according to the rules. Once the controller decides which unit to power, it computes using the unit model the right amount of power to supply. It is important to mention that such amount of power is simply an action order, and may not be automatically feasible for the unit actuator. Therefore, when the next control period comes, a new measure of the real amount of power supply is transmitted to the controller to compute the next action. The energy management rules are described below.

First, if the state of boilers is under or at the minimum limits $\underline{T}_{B,k}$, those are immediately supplied with their allowed maximum power $\overline{P}_{B,k}$.

Then, PV generation is taking into account and managed according a simple priority ladder. PV power is first used to feed non-controllable loads $p_{nc}$. If PV power is enough to supply the building's non-controllable loads, the variable $p_x = p_{PV} + p_{nc}$ refers to the <u>excess</u> free power in the microgrid available to feed flexible loads. Those come second in the PV priority ladder, and the boiler with the lower normalized temperature will be prioritized over the other. Assuming that the controller knows the different temperature limits, it is able to normalize the measured temperature according to those values and compare both boiler states.

When there is no excess power, the supply of non-controllable loads in insured by the grid.

Boilers temperature increase is defined in Equation 8 as a function of power input. By knowing the target temperature $\overline{T}_{B,k}$ and the measured temperature $T_{B,k}[h]$, the controller computes the error $e_k^T[h] = \overline{T}_{B,k} - T_{B,k}[h]$. With the boilers model, this error can be translated to a power, which is the power input needed to attain target temperature.

#### 3.3.1 Pseudocode

**Algorithm 1:** Scenario 1: control of boilers

Executed every time-step $h$
<u>Inputs</u>: $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h], p_{PV}[h], p_{nc}[h], p_{B1}[h], p_{B2}[h]$
<u>Control variables</u>: $\hat{\boldsymbol{u}}_{\boldsymbol{B}}$

**Start**
$p_x = p_{PV}[h] + p_{nc}[h] + p_{B1}[h] + p_{B2}[h]$
*sort* $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h]$ in ascending order
**for** each boiler $k$ **do**
  **if** $T_{B,k} \leq \underline{T}_{B,k}$ **then**
    $u_{B,k} \leftarrow \overline{P}_k$
    $p_x = p_x - p_{B,k} + u_{B,k}$
  **else**
    $e_k^T[h] = max(0, \overline{T}_{B,k} - T_{B,k}[h])$
    $u_{B,k} \leftarrow max[-C_w \frac{e_k^T[h]}{\Delta t}, \overline{P}_k, -(p_x - p_{B,k})]$
    $p_x = p_x - p_{B,k} + u_{B,k}$
    **if** p$_x = 0$ : **break**
  **end**
**end**
*return* Control variables
**End**

## 3.4 Limitations

Being the baseline scenario, the described system presents several limitations. They are summarized in the following points and are related to energy management efficiency, system modelling and controller design/algorithm:

- Inter-interval power variations are not accounted by the controller.
- Very basic modelling of boiler functioning.
- ON/OFF control of boilers' power at lower temperature limit may overstimulate controller's action.
- Excess power might be re-injected into the grid for a lower price if boiler upper limits (both in terms of power and temperature) are attained.

First, the controller acts on the measures obtained at time $h$. It receives those measures and computes the best possible action for time $h$ power state, which may not remain the same during the next $\Delta t$ (until time $h+1$). In the microgrid, power demand can be perfectly matching supply at the beginning of each control action, but this matching ends once non-controllable power supply or demand varies. For instance, if excess is positive, it is supplied to boilers. A few milliseconds later, excess could decrease, forcing the main grid supply some of the power requested by boilers actuators. This would translate into unnecessary costs.

Inter-interval forecasting is a potential solution to tackle the mismatch between microgrid's supply and demand between control time periods. For PV and non-controllable loads power, an ultra short-term forecasting agent would allow to estimate the inter-interval power variations and enable the controller to take actions based on those estimations.

A second limitation which has already been pointed makes reference to the use of a simplistic boiler model. Basically, the model does not account for hot-water consumption and therefore neglects cold water entering the boiler, which is a crucial point when the goal is to control its temperature. Also, outside boiler temperature is not considered and neither are heat losses. Having an incomplete model might give the controller a poor information, and power could be saved by incorporating a model that better describes reality. Eventually, such improved model would allow to use hot water consumption forecasts to further optimize control action.

A third limitation regarding the specific control algorithm has been identified. When handling a boiler at its lower temperature bounds, the controller only reacts when that particular temperature is reached. Because the condition only applies to that unique temperature $\underline{T}_{B,k}$, action stops right after temperature increases even if such increase is small. This behaviour can create a frequent ON/OFF over the boiler, which might overstimulate the EMS and impede a smooth operation.

Finally, capacity limitations might force some of the locally produced power to be re-injected into the grid. If boilers' heat storage capacity is not big enough to absorb all PV power, power re-injected at lower price presents an economic disadvantage if the microgrid is latter in need of that extra power.

# 4 Scenario 2: hysteresis control

In order to improve controllers action around boilers lower bound temperatures, an hysteresis behaviour can be added to controller's logic. Once this limit is reached, a binary variable $s_{B,k}$ is set to 1, which means that the boiler will be supplied until a new temperature target $T_{\Delta,k}$ above $\underline{T}_{B,k}$ is reached. As long as $s_{B,k}$ remains 1, boiler $k$ will be supplied. Once the target temperature $T_{\Delta,k}$ is reached, $s_{B,k}$ will be set equal to 0, meaning that the lower limit temperature constraint has been successfully handled. Boiler will then be exclusively supplied by excess power until its lower bound is reached once again. For handling both boilers, the vector $\hat{\boldsymbol{s}}_{\boldsymbol{B}}$ is defined.

Algorithm 2 presents how the hysteresis process would be implemented in Scenario 2.

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**Algorithm 2:** Scenario 2: control of boilers with hysteresis over lower temperature limits

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Executed every time-step $h$
Inputs: $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h], p_{PV}[h], p_{nc}[h], p_{B1}[h], p_{B2}[h], \hat{\boldsymbol{u}}_{\boldsymbol{B,k}}[h-1]\hat{\boldsymbol{s}}_{\boldsymbol{B}}[h-1]$
Control variables: $\hat{\boldsymbol{u}}_{\boldsymbol{B}}$
**Initialize:** for all $k$: **if**$(T_{B,k}[0] < T_{\Delta,k})$**:** $s_{B,k}[0]$ = 1 , **else:** $s_{B,k}[0]$ = 0

**Start**
$p_x = p_{PV}[h] + p_{nc}[h] + p_{B1}[h] + p_{B2}[h]$
*sort* $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h]$ in ascending order
**for** each boiler $k$ **do**
  **if** $T_{B,k}[h] \geq T_{\Delta,k}$ **then**
    $s_{B,k}[h] = 0$
  **end**
  **if** $T_{B,k}[h] \leq \underline{T}_{B,k}$ **then**
    $s_{B,k}[h] = 1$
  **else**
    $s_{B,k}[h] = s_{B,k}[h-1]$
  **end**

  **if** $s_{B,k}[h] = 1$ **then**
    $u_{B,k} \leftarrow \overline{P}_k$
    $p_x = p_x - p_{B,k}[h] + u_{B,k}$
  **else**
    $e_k[h] = max(0, \overline{T}_{B,k} - T_{B,k}[h])$
    $u_{B,k} \leftarrow max[-C_w \frac{e_k[h]}{\Delta t}, \overline{P}_k, -(p_x - p_{B,k}[h])$
    $p_x = p_x - p_{B,k}[h] + u_{B,k}$
    **if** $\mathrm{p}_x = 0$ : **break**
  **end**
**end**
*return* Control variables
**End**

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# 5 Scenario 3: energy battery storage

Scenario 1 and 2 proposed the base layer to profit from the building's PV installation. By adapting demand to supply, self-consumption could be maximised and therefore power demanded from the grid was reduced. However, at moments when boilers are fully powered or at maximum temperature, some excess power may be re-injected into the grid at a lower price.

A first solution to further maximise self-consumption inconvenience is to install into the building an energy storage battery system. This will add a level of flexibility to the microgrid/building and will be able to shape the power system fluctuations by both consuming and producing power.

Because the battery is only going to step in after the flexible loads have offered their flexibility, a small battery is sufficient. In fact, it is not needed to store all PV power, but rather to give to the microgrid that little extra self-consumption ability. Moreover, putting the battery last in the power supply priority is going to reduce pointless charge/discharge cycles, which are the main source of aging/deterioration.

## 5.1 EMS Components and models

On top of the EMS control architecture required for Scenario 1, the incorporation of the battery adds some complexity to the microgrid. A new control variable needs to be taken into account, and a battery model is needed for the controller to determine the adequate control action.

$$x_b[h+1] = x_b[h] - p_b[h]\,\Delta t \tag{2}$$

$$\underline{C}_b \leq x_b[h] \leq \overline{C}_b \tag{3}$$

$$\overline{P}_b^{ch} \leq p_b[h] \leq \overline{P}_b^{disch} \tag{4}$$

$$\tag{5}$$

New variables and parameters need to be addressed by the EMS. The battery's State-of-Charge (SoC) $x_b$ (kWh) and power $p_b$ (kW) are measured and broadcasted to the controller. The controller communicates back the target power $u_b$ (kW) to be supplied from or demanded to the storage system. The simple battery model presented in Equation 2 allows the controller to set the correct battery power $u_b$ to keep the battery in its limits. Constant parameters are again assumed to be known by the controller. $\overline{C}_b$ and $\underline{C}_b$ are respectively the maximum and minimum battery capacity (kWh). Regarding power limits, $\overline{P}_b^{ch}$ $(\leq 0)$ and $\overline{P}_b^{disch}$ $(\geq 0)$ are respectively the maximum charging and maximum discharging battery power (kW). Regarding the battery model, charging and discharging efficiencies are assumed to be 100%, and no leakage phenomenon is considered.

## 5.2 Control algorithm

Because the battery software is not ideal, it may not able follow all instructions of the controller. To handle that, a normal approach is taken in which control is made according to the real measured quantities $p_b[h]$ and $x_b[h]$. The algorithm takes care of setting actions that remain within the battery constraints 3 and 4.
Like in previous scenarios, controller looks at boilers in case they are at their lower limits. Once this specific case is handled, excess power is supplied to boilers first and battery second. In the case of a negative excess

or demand, the battery supplies the demanded power provided that such demand lies within the battery constraints. If that is not the case, the remaining demand is absorbed by the main grid. Algorithm 3 presents the control logic implemented in Scenario 3.

**Algorithm 3:** Scenario 3: control of boilers and battery

Executed every time-step $h$
Inputs: $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h], p_{PV}[h], p_{nc}[h], p_{B1}[h], p_{B2}[h], \hat{\boldsymbol{s}}_{\boldsymbol{B}}[h-1], p_b[h], x_b[h]$
Control variables: $\hat{\boldsymbol{u}}_{\boldsymbol{B}}, u_b$
**Initialize:** for all $k$: **if**($T_{B,k}[0] < T_{\Delta,k}$)**:** $s_{B,k}[0]$ = 1 , **else:** $s_{B,k}[0]$ = 0

**Start**
$p_x = p_{PV}[h] + p_{nc}[h] + p_{B1}[h] + p_{B2}[h] + p_b[h]$
*sort* $\hat{\boldsymbol{T}}^{\boldsymbol{B}}[h]$ in ascending order
**for** each boiler $k$ **do**
  **if** $T_{B,k}[h] \geq T_{\Delta,k}$ **then**
    $s_{B,k}[h] = 0$
  **end**
  **if** $T_{B,k}[h] \leq \underline{T}_{B,k}$ **then**
    $s_{B,k}[h] = 1$
  **else**
    $s_{B,k}[h] = s_{B,k}[h-1]$
  **end**

  **if** $s_{B,k}[h] = 1$ **then**
    $u_{B,k} \leftarrow \overline{P}_{B,k}$
    $p_x = p_x - p_{B,k}[h] + u_{B,k}$
  **end**
**end**

**for** each boiler $k$ **do**
  **if** $p_x \geq 0$ **and** $s_{B,k}[h] = 0$ **then**
    $e_k[h] = max[0, (\overline{T}_{B,k} - T_{B,k})]$
    $u_{B,k} \leftarrow max[-C_w \frac{e_k[h]}{\Delta t}, \overline{P}_k, -(p_x - p_{B,k}[h])]$
    $p_x = p_x - p_{B,k}[h] + u_{B,k}$
  **end**
**end**
**if** $p_x \geq 0$ **then**
  u$_b \leftarrow max[\frac{x_b[h] - \overline{C}_b}{\Delta t}, \overline{P}_b^{ch}, -(p_x - p_b[h])]$ (charge battery)
**else**
  $u_b \leftarrow min[\frac{x_b[h] - \underline{C}_b}{\Delta t}, \overline{P}_b^{disch}, -(p_x - p_b[h])]$ (discharge battery)
**end**
*return* Control variables
**End**

## 5.3 Limitations

The incorporation of a battery system is able to tackle one of the limitations of previous scenarios and therefore increase self-consumption. However, it also introduces a new challenge for future scenarios, which is to bring a more accurate battery model. Important parameters such as charging and discharging efficiencies as well as battery leakage coefficient have not been considered in the present scenarios. By implementing a better model, a more precise control action could enhance battery usage and make the EMS more efficient.

# 6 Scenario 4: accurate energy models

(don't know if I should present the more accurate battery model. there, i consider its charging efficiency, but in the new boiler model i don't consider the "electrical" efficiency). check real values of battery charging efficiencies.

Although the system described in Scenario 3 has the capabilities to control both the batteries and the boilers, there is no guarantee that the control of the devices is optimal and the operation is secure. Because of the simplifications made when modelling such units, it may happen that the control action is not well adapted to their real state. For instance, when the boiler is approaching its upper temperature limit, its power supply may start diminishing sooner than it would ideally have to. This is due to the fact that the model does not account for thermal losses, and so the real temperature increase for a certain power is less than the modelled one.

Defining more accurate models makes the EMS more aware of the individual necessities and constraints of the units, and improves the comfort and the energy efficiency of the building as whole.

The new SoC evolution of the battery can be described with the following model:

$$x_b[h+1] = \alpha_b \; x_b[h] + \eta_b^+ \; u_b^+[h] + \eta_b^- \; u_b^-[h] \; \Delta t \tag{6}$$

$$\begin{aligned} u_b^+[h] &= \max(0, u_b) \\ u_b^-[h] &= \max(0, -u_b) \end{aligned} \tag{7}$$

Such a model introduces a battery leakage coefficient $\alpha_b$ that represents the battery capacity to retain its energy (which is not ideally set to 100% anymore). It is the opposite of the rate at which the battery self-discharges per time period. Typically, lithium-ion batteries have a 3% self-discharge per month. Furthermore, $\eta_b^+$ and $\eta_b^-$ are respectively the battery discharging and charging efficiencies. The power and capacities constraints defined in 4 and 3 remain the same.

Regarding the boilers, a more detailed model that considers hot water consumption and thermal losses is considered. The hot water tank is modelled as a volume of water with a homogeneous temperature, across the whole tank. Its temperature variation is not only a function of the power input, but also of the hot-water consumption, the ambient temperature and the inlet temperature, which are supposed to be measured by pre-existing or incorporated sensors. Equation 8 presents the discrete evolution of boiler's temperature.

$$\begin{aligned} T_{B,k}[h+1] = e^{-\frac{\Delta t}{R[h] C_w}} \; T_{B,k}[h] + (1 - e^{-\frac{\Delta t}{R[h] C_w}}) \; R[h] \; u_{B,k}[h] \\ + (1 - e^{-\frac{\Delta t}{R[h] C_w}}) \; R[h] \; \begin{bmatrix} U & d_{B,k}[h] \end{bmatrix} \begin{bmatrix} T_a[h] \\ T_{c,k}[h] \end{bmatrix} \end{aligned} \tag{8}$$

In Equation 8, $C_w$ is the water tank thermal capacity, $R[h] = (U + d_{B,k}[h])^{-1}$ is the equivalent water-to-exterior resistance that takes into account the thermal losses $U$ and water withdrawal $d_{B,k}[h]$ (in $(l/s)$) from boiler $k$ at time $h$ . $T_a$ and $T_{c,k}$ respectively stand for the ambient air temperature, which is assumed to be homogeneous, and the inlet cold water temperature. The efficiency of the electrical system is assumed to be 1.

## 6.1 Control Algorithm

The logic behind Scenario's 3 algorithm remains unchanged. With the new models, the controller is simply able to compute more accurate actions.

In the boiler model, because $T_a[h]$, $T_{c,k}$ and $d_{w,k}[h]$ are measured quantities, $T_{B,k}[h+1]$ is in the eyes of the controller a function of the supplied power $u_{B,k}[h]$. This new control action is defined in Algorithm 4 as $u_{B,k}$ s.c $T_{B,k}[h+1] = \overline{T}_{B,k}$. Similarly, the control action over the battery with the objective to bring it to the upper limit can be written as $u_b$ s.c $x_b[h+1] = \overline{C}_b$ (respectively $\overline{C}_b$ when discharging and looking to reach lower limits). Modification from Algorithm 3 to Algorithm 4 are highlighted in red below.

**Algorithm 4:** Scenario 4: control of boilers and battery

Executed every time-step $h$

Inputs: $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h], p_{PV}[h], p_{nc}[h], p_{B1}[h], p_{B2}[h], \hat{\boldsymbol{s}}_{\boldsymbol{B}}[h-1], x_b[h], p_b[h], d_{w,k}[h], T_a[h], \hat{\boldsymbol{T}}_{\boldsymbol{c}}$

Control variables: $\hat{\boldsymbol{u}}_{\boldsymbol{B}}, u_b$

**Initialize:** for all $k$: **if**($T_{B,k}[0] < T_{\Delta,k}$)**:** $s_{B,k}[0]$ = 1 , **else:** $s_{B,k}[0]$ = 0

**Start**

$p_x = p_{PV}[h] + p_{nc}[h] + p_{B1}[h] + p_{B2}[h] + p_b[h]$

*sort* $\hat{\boldsymbol{T}}^{\boldsymbol{B}}[h]$ in ascending order

**for** each boiler $k$ **do**
- **if** $T_{B,k}[h] \geq T_{\Delta,k}$ **then**
  - $s_{B,k}[h] = 0$
- **end**
- **if** $T_{B,k}[h] \leq \underline{T}_{B,k}$ **then**
  - $s_{B,k}[h] = 1$
- **else**
  - $s_{B,k}[h] = s_{B,k}[h-1]$
- **end**
- **if** $s_{B,k}[h] = 1$ **then**
  - $u_{B,k} \leftarrow \overline{P}_{B,k}$
  - $p_x = p_x - p_{B,k}[h] + u_{B,k}$
- **end**

**end**

**for** each boiler $k$ **do**
- **if** $p_x \geq 0$ **and** $s_{B,k}[h] = 0$ **then**
  - $e_k[h] = max[0, (\overline{T}_{B,k} - T_{B,k})]$
  - $u_{B,k} \leftarrow max[u_{B,k}$ s.c $T_{B,k}[h+1] = \overline{T}_{B,k}, \overline{P}_k, -(p_x - p_{B,k}[h])]$
  - $p_x = p_x - p_{B,k}[h] + u_{B,k}$
- **end**

**end**

**if** $p_x \geq 0$ **then**
- $u_b \leftarrow max[u_b$ s.c $x_b[h+1] = \overline{C}_b, \overline{P}_b^{ch}, -(p_x - p_b[h])]$ (charge battery)

**else**
- $u_b \leftarrow min[u_b$ s.c $x_b[h+1] = \underline{C}_b, \overline{P}_b^{disch}, -(p_x - p_b[h])]$ (discharge battery)

**end**

*return* Control variables

**End**

## 6.2 Limitations

Even if the new models are slightly more complex, they do not introduce computationally expensive operations for the controller. However, given that those models are not perfect representation of reality, many limitations can be spotted again. For instance, electrical efficiencies are assumed to be 1 for the boilers, and inside temperature is assumed to be homogeneous. Further improvements of such models would require investigating corresponding research fields, which goes outside the scope of this report. Modelling limitations are therefore solved at this point.

However, now that losses in the boilers are accounted, the possibility to effectively manage such equipment in order to minimize losses arises. The higher the boiler temperature, the more energy is going to be lost due to thermal losses. Hence, it may not be ideal anymore to keep the boiler at its highest temperature when it is not going to be used over a long period of time. Here is where a planning based on long-term forecasts would be advantageous. One could imagine that in summer, if the EMS knows that PV power is going to be abundant and boiler 2 is practically not going to be used, the system may avoid oversupplying such boiler and instead profit from feeding back the excess power to the grid. This remains a limitations to be treated in future scenarios.

# 7 Scenario 5: Ultra-short term forecast

BIG ISSUE TO CORRECT. NEVERMIND THIS SCENARIO. BOILERS CONTROL ALSO NEEDS TO BE DONE CONSIDERING FORECAST.
By introducing forecasts, unpredictable non-controllable variables can be estimated with a certain accuracy. Supplying the energy management system with a ultra-short-term forecast (i.e. 2 minutes) could therefore help the system to handle inter-interval power variations in the building.

In this scenario, an ultra short-term forecast system for PV and non-controllable loads is introduced. Regardless of their algorithm, it is assumed that forecasts provide the EMS with their most likely estimation. The EMS then perform its jobs assuming that the received estimation is a true prediction of the microgrid future state. Because such assumption can be far from reality, the error will translate into some excess power demanded from or supplied to the grid. The more accurate is the forecast, the more exact will be the matching of supply and demand in the building.

In this scenario, hot water consumption is not forecasted and so the power supply of boilers remains as in previous scenarios.

## 7.1 Control Algorithm

With hot water consumption forecasts $\hat{d}_{w,k}[h+1]$ and ambient temperature $\hat{T}_a[h+1]$ forecasts, the power needed to bring boilers to their future desired state can be computed. Those power predictions are noted $\hat{p}_{B,k}[h+1]$. Adding the forecasts of demanded non-controllable power $\hat{p}_{nc}[h+1]$, supplied solar PV power $\hat{p}_{PV}[h+1]$, the predicted excess power $\hat{p}_x[h+1]$ can be computed. For that calculation, it is assumed that battery power remains constant at $p_b[h]$, its previous interval value. This allows to quantify with $\hat{p}_x[h+1]$ the excess that the battery has to handle with from now on to the next control period.

During that inter-interval time, the controller assumes a linear variation of excess power, going from the excess $p_x[h]$ measured at time $h$ to the excess $\hat{p}_x[h+1]$ predicted at time $h+1$. Such excess prediction is computed accounting for all individual predictions at time $h+1$ (PV, non-controllable, and Although the matching may not be ideal, it may improve self-consumption.

Assuming that linear variation of excess power, the new algorithm computes a single set of actions for every time-step $h$. However, such set is now composed of several discrete actions, whose quantity depend on the operating frequency ($1/dt$) of the BMS. For instance, a typical BMS works in the millisecond range. The action $u_b(t_b)$ computed by the controller at time $h$ will then be composed by multiple inter-interval actions of length $dt$.

I WILL DRAW AN INTER-INTERVAL GRAPH SHOWING THE DIFFERENCE BETWEEN THIS AND PREVIOUS SCENARIOS .

It can be seen in Algorithm 5 that the action procedure to charge or discharge the battery is computed for every BMS timestep $dt$. (If too computationally expensive, such *for* loop could be avoided. Instead, the system could only consider the battery initial state $x_b[h]$ to compute the power needed to keep the storage device within its limits. With such an algorithm, the match between excess and battery power will not be perfectly accurate when approaching SOC limits. )

**Algorithm 5:** Scenario 5: Inter-interval control using forecasts

Executed every time-step $h$

Inputs: $\hat{\boldsymbol{T}}_{\boldsymbol{B}}[h], p_{PV}[h], p_{nc}[h], p_{B1}[h], p_{B2}[h], \hat{\boldsymbol{s}}_{\boldsymbol{B}}[h-1], x_b[h], p_b[h], d_{w,k}[h], T_a[h], \hat{\boldsymbol{T}}_{\boldsymbol{c}}, \hat{p}_x[h+1], \hat{p}_{PV}[h+1], \hat{p}_{nc}[h+1], \hat{d}_{w,k}[h+1], \hat{T}_a[h+1]$

Control variables: $\hat{\boldsymbol{u}}_{\boldsymbol{B}}, u_b(t_b)$

**Initialize:** for all $k$: **if**($T_{B,k}[0] < T_{\Delta,k}$)**:** $s_{B,k}[0]$ = 1 , **else:** $s_{B,k}[0]$ = 0

**Start**

$\mathrm{u}_b(t_b) = 0$

$p_x = p_{PV}[h] + p_{nc}[h] + p_{B1}[h] + p_{B2}[h] + p_b[h]$

*priority for boilers as usual (see Algorithm 4). They are supplied independently of the forecast.*

$\hat{p}_x[h+1] = \hat{p}_{PV}[h+1] + \hat{p}_{nc}[h+1] + \hat{p}_{B1}[h+1] + \hat{p}_{B2}[h+1] + p_b[h]$

$excess(t_b) = p_x + \frac{\hat{p}_x[h+1] - p_x[h]}{\Delta t}\, t_b$ (function of inter-interval discrete time $t_b$)

**for** $t_b \in [h; h+1]$ **do**

  compute $x_b(t_b + dt)$ using $u_b(t_b) = excess(t_b)$ (Battery model, equation 6)

  **if** $excess(t_b) \geq 0$ **then**

    compute $P_{SOC}^{lim}$ s.c $x_b(t_b + dt) = \overline{C}_b$

    $u_b(t_b) = max[P_{SOC}^{lim}, \overline{P}_b^{ch}, -excess(t_b)]$

  **else**

    compute $P_{SOC}^{lim}$ s.c $x_b(t_b + dt) = \underline{C}_b$ (Battery model, equation 6)

    $u_b(t_b) = min[P_{SOC}^{lim}, \overline{P}_b^{disch}, -excess(t_b)]$

  **end**

**end**

$u_b \leftarrow u_b(t_b)$

*return* Control variables

**End**

# 8 Scenario 6: MPC

Previous scenario presented an EMS capable of using a short-term prediction of the future. It capitalized on it by ensuring that demand matched supply between two successive calls of the controller algorithm.

The benefits of introducing a 24 hours forecast are more notorious. In such a scenario, energy management stops being a myopic problem and a more cost-effective approach can be taken. For the first time, the variable cost of power demanded from and supplied to the grid can be taken into account. With an estimation of daily power needs, the scheduling of controllable loads can be optimized to reduce the electricity bill.

The cost of power demanded from the grid is a variable function $C_{buy}[h]$ that can take different values according to the period of the day. In this scenario, it is assumed that the grid operator presents a day-ahead price, meaning that $C_{buy}[h]$ is known 24 hours in advance. Similarly, $C_{sell}[h]$ is the price set by the grid to re-buy excess electricity produced by the building. This price function is also variable, and can even get negative during certain periods of the day. For instance, depending on the contract, certain solar PV owners in Switzerland have to pay if they inject power into the network at mid-day.

Because predictions such as the forecasted PV power are subjected to uncertainties, performing a single optimization at time t=0 to determine the whole 24 hours schedule may end up not being optimal once the day starts. Such schedule would be computed accounting for different predictions that might be far from the true values. To solve that issue, a model predictive control (MPC) approach is taken in this scenario.

In model predictive control techniques, models of a process as well as future predictions of performance and external variables are use in order to determine controls signals by minimizing an objective function at each step. This optimization problem gives at each step a control sequence, from which only the first one is implemented. At next time step, the optimization horizon moves away from one period and a new sequence is computed. MPC adapts to the uncertainty of the prediction since the implemented action always incorporate the latest observation of the state.

### 8.0.1 EMS components and systems

The logic being model predictive control can be seen with the example of the boiler. The estimated water consumption $\hat{d}_{w,k}[h : h + H - 1]$ and ambient temperature $\hat{T}_a[h : h + H - 1]$ allow the MPC to anticipate and compute the next control actions $u_{B,k}[h : h + H - 1]$ that minimize the cost integrated over the horizon H, assuming the disturbances will be $\hat{d}_{w,k}[h : h + H - 1]$ and $\hat{T}_a[h : h + H - 1]$. Then, when the real disturbances $d_{w,k}[h]$ and $T_a[h]$ reveal, the model allows to compute boiler's next temperature state $T_{B,k}[h + 1]$.

Contrary to previous scenarios, the interval period of this control strategy needs to be big enough to allow a linear optimization problem to be solved. It is assumed that units are able to reach their target power within a time period which is negligible when compared to the MPC period (i.e. $1s\ vs.\ 10min$). The inefficiencies resulting of this transitory state are neglected and the MPC can be written as follows:

$$min_{\hat{\mathbf{u}}_{\mathbf{B}},u_b} \sum_{h=0}^{H-1} C_{buy}[h]\, p_g^+[h] - C_{sell}[h]\, p_g^-[h] \tag{9a}$$

$$s.t.$$

$$p_g[h] + \hat{p}_{PV}[h] + \hat{p}_{nc}[h] + \sum_{k=1,2} u_{B,k}[h] + u_b[h] = 0 \tag{9b}$$

$$p_g^-[h] = max(0, -p_g[h]) \tag{9c}$$

$$p_g^+[h] = max(0, +p_g[h]) \tag{9d}$$

$$u_b^+[h] = \text{max}(0, u_b[h]) \tag{9e}$$

$$u_b^-[h] = \text{max}(0, -u_b[h]) \tag{9f}$$

$$x_b[h+1] = \alpha_b\, x_b[h] + \eta_b^+\, u_b^+[h] + \eta_b^-\, u_b^-[h]\, \Delta t \tag{9g}$$

$$\underline{C}_b \leq x_b[h] \leq \overline{C}_b \tag{9h}$$

$$\overline{P}_b^{ch} \leq u_b[h] \leq \overline{P}_b^{disch} \tag{9i}$$

$$0 \leq u_{B,k}[h] \leq \overline{P}_{B,k} \quad \text{for } k = 1, 2 \tag{9j}$$

$$T_{B,k}[h+1] = A\, T_{B,k}[h] + B\, u_{B,k}[h] + C\, \hat{d}_{B,k}[h] \quad \text{for } k = 1, 2 \tag{9k}$$

$$\underline{T}_{B,k} \leq T_{B,k}[h] \leq \overline{T}_{B,k} \quad \text{for } k = 1, 2 \tag{9l}$$

$p_g$ stands for grid supply to or demanded from power. The sign "+" in $p_g^+$ points that it is a positive variable, and that the building is taking power from the grid to supply its loads. This can be formulated as: $p_g^+ = max(0, +p_g)$. Similarly, $p_g^- = max(0, -p_g)$ is power that is injected into the grid.