The presentation of a model-based predictive controller architecture through the interfacing of a dynamic simulation platform DIMOSIM and an optimization modeller OMEGAlpes

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Abstract

Energy context of today is growing in complexity. This increasing complexity leads research to investigate into innovative control strategies. Indeed those strategies are trump cards to guarantee energy performances dealing with these challenges. Anticipative controllers, such as model-based predictive controllers, provide many assets considering these specificities. This paper presents the development of a Model Predictive Control (MPC) architecture which bases its controller on an optimization MILP modeller, OMEGAlpes. This architecture is tested by interfacing this modeller with a bottom-up dynamic simulation platform for district energy calculations, DIMOSIM. The paper describes the methodology and concept of the MPC architecture as well as the coupling with DIMOSIM used as district emulator. An analysis of a textbook case compares its efficiency to a classic reactive controller.

Introduction

A moving energy landscape

According to a European Union study1, “buildings are responsible for approximately 40% of energy consumption and 36% of CO2 emissions in the EU. Currently, about 35% of the EU’s buildings are over 50 years old and almost 75% of the building stock is energy inefficient”.

This observation compel the stakeholders to focus on energy efficiency and renewable energies (such as PV, wind or biogas) in their urban-scaled decisions. The energy landscape is constantly evolving: new actors appear as well as innovative storage devices (electric vehicles, Power to gas, geothermal storage). Consequently, appropriated energy management strategies are developed for an urban scale (centralized, decentralized, mixed). Energy networks are becoming more and more flexible and complex. Reactive control applied to energy management issues could turn out to be inefficient in the near future.

A need of more flexible control systems

In this context, new control strategies have been developed in order to handle this complexity in time and space. That kind of controller became feasible thanks to the major breakthrough in data mining (machine learning, deep learning). These methods allow anticipative control, which is very promising for the energy systems of today. In this paper, we consider one method of anticipative control, the MPC. Their capability to take into account predictable disturbances with data mining (weather, people behaviour…) appears to be a great strength.

In this paper, the ultimate goal is to settle the theoretical foundation and concept of a MPC architecture in order to handle both district and building levels.

Paper structure

First, the paper defines the different control command strategies and the types of control. It precedes a focus on MPC and its general architecture. Then, it depicts the simulation platform DIMOSIM and the optimization modeller OMEGAlpes. Afterwards, it presents the developed MPC architecture as well as the interfacing between the MPC and the DIMOSIM as district emulator. It ends with the details of a textbook study which highlights some assets of the presented MPC architecture.

Methods

New strategies of control for the district scale

Centralised control strategies have already been implemented at district scale (Dieckman et al., 2017). They impose an overall control strategy for all the systems in a considered district. That kind of control considers the district as a whole.

On the other hand, decentralised strategies have proven their efficiency at the building level (Hassan et al., 2016). Besides, tests have started at the district level through microgrid concepts (Alizadeh et al., 2017). Here the whole district is scattered into smaller systems (at building scale) that possess their own controller.

Another possible control strategy consists in a compromise of those two (Mao, 2017). At district level, the concept is to divide the global system into smaller ones. Each of them would possess their own control strategy. Then, a meta-controller orchestrates all these controllers and enables their interoperability with a bottom-up hierarchical logic.

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1https://ec.europa.eu/energy/en/topics/energy-efficiency/buildings
Reactive control vs Anticipative control

Reactive control (Oriti et al., 2015), the control system reacts to disturbances in order to keep the controlled value around its set point. Those controllers work accordingly to the current and past behaviour of the system. Even if the management is ingeniously developed, they have no means of predicting its future behaviour.

By introducing anticipation in the loop, the control seems to gain robustness towards complex systems. Here, the focus is on MPC strategies. The principle of this technique (Han et al., 2018) consists in using the prediction(s) made by a prediction model based on the considered system. Those predictions serve as input for an optimisation. Thus, the model anticipates the future behaviour of the system, which allows the optimiser to choose a pseudo-optimal control signal. The prediction time is called the horizon of the prediction and corresponds to the period during which each optimization is made.

The generic MPC architecture

The aim of a control system is to be plugged at any system. Considering the reactive controller, their characteristics make them easy to implement. Indeed, they react to the output of each system and determine control decision consequently.

The problem with anticipative controller such as MPC lies on the data management it needs. Indeed, in at a district scale, each system will send their data measurements sporadically. Consequently, the data measurement will be asynchronous. Thus, a module of synchronisation would be necessary in the process.

In the considered MPC architecture, as illustrated on figure 1, the MPC procedure lies on a general orchestrator. This MPC uses as a basic component a Prediction control Model (P.C.M.). The orchestration is activated thanks to a data receiver that provides the inputs for each element of the MPC. The predictor module predicts the future behaviour of external parameters either external conditions (e.g. weather conditions) or internal loads (e.g. Domestic Hot Water Load). Then, the orchestrator activates the estimator which determines for the P.C.M. both the parameter of the model (p.m.) and the values of the state variables (s.v.). Afterwards, the optimization model controller (O.P.C.) exchanges with the P.C.M. in order to settle the optimized Control Variables (c.v.). This procedure ends with the sending of the set of control command and an update of the database related to the received measurement.

Figure 1 illustrates the main principle of a model-based predictive controller.

![Figure 1: General principle of model-based predictive controller architecture](image-url)
Considering our problematic, the focus is made on the MPC architecture and its relevance at a district scale. The part considering the synchronization of data measurements would be considered as a future improvement. That is why a simulation would be used as an emulation of a district in future work. The simulation would be ruled by the simulation platform DIMOSIM.

The simulation platform DIMOSIM - emulator of the district energy system

Dimosim (Riederer et al., 2015) is a bottom-up dynamic simulation platform for energy systems in districts. It has been developed since 2014 by the CSTB (www.cstb.fr). This tool is built on an object-oriented structure. The building and energy component (production, storage, networks) models are based on physical description with a level of detail that has been selected specifically for the district and urban scale. The tool is based on power flows and typically used infra-hourly time steps.

The tool has been developed thanks to the European projects Resilient and SmartMedParks for the application on conception (SmartMedParks) and operation (Resilient) studies.

A communication layer has been added to the Dimosim platform in order to allow the interfacing of controllers (that can be MPC or more classical reactive controllers) since the early beginning of its development. This is used in this paper to connect the MPC controller to DIMOSIM.

The optimization modeller OMEGAAlpes – optimiser used for the implementation of our MPC controller

OMEGAAlpes is an optimization modeller based on MILP (Fan and Sadat, 2017)) optimization models created by the G2Elab. The software is using pulp (Mitchell et al., 2011) method as a solver library, but it can use other solvers such as GUROBI (Ringkjøb et al., 2018).

The model relies on energy unit blocks divided into three main categories: producer unit, consumer unit and storage unit. Each energy unit possesses their own set of constraints accordingly to their types. Those units can be either fixed or variable (Pajot et al., submitted to BS 2019).

Fixed unit get a fixed power profile as an input. Depending on the context, either measurements or predictions can provide those profiles. Variable units are determined according to their set of constraints. The optimization model will then determine their profile.

An energy node interconnects blocks together. Depending on the system, the optimisation could consist in several nodes, which would be interconnected. To finalize the model, any energy unit can integrate a cost function. The minimization of those functions would have a direct impact on the linked parameters. All those cost functions are added to finalize the objective function.

Figure 2 illustrates the modelling principle used for OMEGAAlpes models.

The optimization model is a combination of:

- a block structure of energy units interconnected by energy nodes
- a set of constraints and state equations related to each energy unit

Complex MPC schemes at a district level consisting in an orchestration of several models are feasible. The following part presents a district emulation architecture for a textbook study. It highlights the concept and theory of such an architecture.

District emulation architecture for the textbook study of the developed MPC optimiser

At first, a specific class of DIMOSIM enables to configure the data exchange between the simulation and an external controller, here the MPC controller. A socket manager interfaces the two tools. The socket interface allows to exchange data between the district emulator and the MPC controller. They provide a form of inter-process communication (IPC). The network can be a logical, local network to the computer, or one that is physically connected to an external network, with its own connections to other networks (Gordon M., 2005).

Figure 3 depicts the functioning of the data exchange between DIMOSIM and MPC:

At each time step of DIMOSIM, the sequencing achieves an optimization. In that case, an interface is used to coordinate the exchanged data through the socket.

The pre-process provides to the optimization model a preliminary dataset. This dataset is necessary to run an optimization. Data treatment takes into account the specific time step of both optimization and simulation.

2 https://docs.python.org/2/library/socket.html
model. Once the model is completed, an optimization run on the horizon of MPC.

As a result, the simulation receives the optimized control signals. Then, the simulation proceeds to the next time step, until the end of the simulation.

**The textbook case study**

Here we focus at the building level in order to test the efficiency of the MPC architecture on a textbook case. The choice of a simple system was motivated by the ease of implementation and the clarity of results for verification.

A house composed of two dwellings is considered. The domestic hot water (DHW) for both dwellings is provided by a solar domestic hot water system composed of a 0.2 m$^3$ water tank connected to thermal solar panels (net area of the solar collector of 2m$^2$) and a 1 kW back-up heater. The system is studied during 3 days resulting a solar hot water production of 21 kWh and a hot water demand of 58 kWh.

The objective is to control the back-up system in order to fulfil the needs of the occupants (thus guarantee the DHW comfort temperature and volume) while minimising the overall consumption of the backup heater. The reference solution, for comparison is the default (classic reactive control) control of the simulation platform DIMOSIM.

**Performance indicators for the evaluation**

Three performance indicators have been selected. First, the total energy consumed by the backup heater during the simulation time $T$:

$$E_{BU} = \sum_{t=0}^{T} \Phi_{BU}[u][t] \tag{1}$$

Where $\Phi_{BU}[u][t]$ is the backup heater power at each time step $t$.

Second, the availability of the DHW that corresponds to the number of time steps when the tank temperature is lower than the minimum acceptable value during the simulation time $T$:

$$A = \sum_{t=0}^{T} (d^1[t]), \tag{2}$$

where $d^1[t]=\begin{cases} 1, & \text{if } T_{WT}[t]<T_{WT, min} \\ 0, & \text{else} \end{cases}$

Where $T_{WT}[t]$ is the average temperature inside the tank at the time step $t$ and $T_{WT, min}$ is the minimum acceptable DHW temperature.

Finally, the usability of the DHW that corresponds to the number of time step when the tank temperature is higher than the minimum acceptable value in the same time than a demand for DHW:

$$U = \sum_{t=0}^{T} (1-d^1[t])u^1_{load}[t] \tag{3},$$

where $u^1_{load}[t]=\begin{cases} 1, & \text{if } \Phi_{load}[t]>0 \\ 0, & \text{else} \end{cases}$

Where $\Phi_{load}[t]$ is the DHW load at each simulation time step.

**The development of the MPC architecture applied on the textbook study**

First, the solar domestic hot water system is modelled in DIMOSIM in the following way:

- a physical, transient model of the storage tank with 3 vertical nodes;
- a polynomial based steady state solar collector model based on measurement (certified a0, a1 and a2 coefficients);
- a simple on-off control of the solar circulation pump for charging the storage tank;
- an electric backup heater (ideal with 100% efficiency);
- a DHW hot water draw has been generated by a load generator in DIMOSIM. The generator, based on French hot water usage statistics, produced a stochastic hot water draw profile in terms of draw demand (in W);
- a solar energy processing unit that calculates solar direct and diffuse radiation incident to the solar collector (characterized by an angle of inclination and azimuth, chosen as ...).

The backup heater is controlled using an on-off controller with hysteresis. The backup controls the storage tank to a fixed setpoint of 60°C. The chosen hysteresis is 2.5K.

The simulation runs from January 12 to 15 at Nice, France.

Hereafter the results from the simulation:

![Figure 4: Results plots from DIMOSIM simulation of the textbook study (reference case)](image)

The first graph shows in orange the DHW load and the thermal solar production within the three days of study. The second one corresponds to the variation of the mean tank temperature. The third graph depicts the behavior of the control system (control command of the backup heater).

Here is translated the behavior of a reactive control, which is activated from 57.5°C to 62.5°C. The hypothesis of an external temperature constantly equal to 20°C explains the pseudo-linear losses. Here, the backup consumes 7.8 kWh, the availability value reaches 70% and the usability value reaches 53%.

Considering the textbook study, the optimization model relies on the following state equation:

$$m_{WT} \cdot C_p_{water} \cdot \frac{dT_{WT}[t]}{dt} = \Phi_{load}[t] + \Phi_{Solar}[t] + \Phi_{BU}[t] + U_{WT} \cdot A_{WT} \cdot (T_{WT}[t] - T_{ext}) \tag{4}$$

Where $m_{WT}$ is the mass of water in the tank, $C_p$ is the specific heat of water, $T_{WT}$ is the average temperature...
inside the tank at the time step $t$. $\phi_{\text{Solar}}$ represents the power flow from the solar panels, $\phi_{\text{BU}}$ represents the power flow from the backup, $\phi_{\text{Load}}$ represents the power flow from the consumption, $U_{WT}$ represents the loss coefficient of the water tank, $A_{WT}$ represents the area of the water tank.

Hereafter the OMEGAAlpes map of the textbook study:

**Figure 5:** A map describing the optimization model of the water tank

The storage unit is commonly constrained by upper and lower bounds. In a MPC scheme, keeping the lower bound would lead to a reaction close to the control simulation. Indeed the tank temperature is strictly maintained above the lower bound. The constraint would be taken into account into the objective function of the optimization model.

Here we consider a problem with two antagonist objectives:
- Minimizing the backup consumption
- Maximizing the comfort of the users

Those objectives are weighted by a scalar factor alpha leading to a mono-objective problem.

The following optimization function is considered:

$$\min_\alpha E_{BU} + (1 - \alpha) U$$  \hspace{1cm} (5)

Where $\alpha \in [0, 1]$

Thus, the simulation sends the data measurement considering the DHW load, the solar production, the backup profile and the temperature from the beginning of the simulation until the considered time step $t_{\text{init}}$.

Both DHW load and solar production measurements are inputs for the external predictor. They are processed in a way to obtain their future profile until the horizon time $t_h$ considering the current time step $t_{\text{init}}$.

All the data measurements serve as an input of the identifier. Most of the time, a parameter estimator and a state initializer constitute separately the identifier. However, some conditions can lead to a single identifier, which manages the two roles at the same time. Anyway, the identifier relies on the prediction model, which corresponds to the state equation of the system.

External predictor and identifier are the pre-process treatment in this MPC architecture. They provide to the optimiser the inputs it needs to run. The optimiser coupled with the prediction model manages to solve the problem. The native MILP solver validates the optimised solution within a set of predicted scenarios.

Then DIMOSIM receives the optimized command signal of the backup and applies it. This overall process loops until the end of the simulation.

Hereafter, a graph of this sequencing:

**Figure 6:** Sequential scheme of the developed MPC architecture

The investigation to find a compromise between energy consumption and comfort

As two antagonist objectives are considered, a paretan assessment enables to find the best compromise (Ngatchou et al., 2005). The principle is to optimize the case within the alpha spectrum. The optimization of the water tank runs on the three days of study.

The Pareto assessment relies on two indicators for its processing. The first one corresponds to the energy consumed by the backup on the three days of study.

The other one corresponds to a variation of the usability indicators as follow:

$$\sum_{t_{\text{init}} + k}^{t_{\text{end}} + k} m_{WT} \cdot c_p \cdot T_{WT}[t] \cdot (1 - \frac{T_{WT}[t]}{T_{WT, min}}) \cdot u_{\text{Load}}[t]$$  \hspace{1cm} (6)

where $u_{\text{Load}}[t] = \begin{cases} 1, & \text{if } \delta_{\text{Load}}[t] > 0 \\ 0, & \text{else} \end{cases}$

Where $T_{WT, min}$ is the minimal of usage, $T_{WT}[t]$ is the average temperature inside the tank at the time step $t$.

The value of each indicator for alpha between 0 and 1 allows a normalisation of this study. These values correspond to the higher value the indicator can take in this study space. For alpha equal to 1, the optimization is made by only considering the backup consumption, without any constraints concerning the mean value of tank temperature. The value obtained is 6,1 kWh. For alpha equal to 0, the optimization is made by considering the usability. The value obtained is 7 950 kWh. Then, for the other alpha, the resulting indicators of backup consumption and usability are divided by the normalized value determined with alpha equal to 0 or 1.

Hereafter the results from the Pareto evaluation where alpha is varying from 0 to 1 with normalized results:
It seems that a compromise is around an alpha value of 0.45 close to the inflexion part of the Pareto curve.

**Results**

**Ideal choices for the first implementation of the MPC architecture**

As previously presented, the optimization model consists in a one-layer water tank while the model of DIMOSIM consists in three layers water tank. In order to suppress this difference, the model in DIMOSIM has been downgraded to a one-layer water tank.

Considering the MPC, the predictor is perfect. Indeed a previous identical simulation provides a perfect forecast behavior. Then, the data coming from DIMOSIM enables to know perfectly the system parameters. The socket transmits as an input for optimization. Text files store those data, and pre-treatment consists in transferring them as an input for optimization.

Finally, the DIMOSIM model enables the transmission of the state of the system, here the mean temperature of the water tank. Thanks to the socket connection, the optimization model receives the state initialization at each time step.

The optimization determines a predicted set of backup command according to it cost function. Then, DIMOSIM receives the optimized backup command. The simulation goes on until the next time step.

For further validations, resetting the differences between the two models, including errors within the prediction or estimating parameters and state of the system thanks to the state equation of the system can improve the MPC scheme.

**Results from the study on the horizon effect on the efficiency of MPC**

For this study, we have fixed the time step at 10 minutes for both models. The horizon effects on the MPC efficiency is the subject of this study. The higher the horizon is, the further we can predict and optimize the behavior of the system. The counterpart of a high prediction horizon leads to an increase of prediction errors. This is why the prediction was set as perfect. This allows focusing on the efficiency of MPC in perfect conditions. So, we expect that increasing the length of the horizon would increase the performances of the MPC. Hereafter a table resuming the study made on the horizon:

<table>
<thead>
<tr>
<th>Energy Consumption</th>
<th>Horizon</th>
<th>2h</th>
<th>4h</th>
<th>6h</th>
<th>8h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usability</td>
<td>DIMOSIM</td>
<td>53%</td>
<td>50%</td>
<td>34%</td>
<td>40%</td>
</tr>
<tr>
<td>Availability</td>
<td>DIMOSIM</td>
<td>10%</td>
<td>5%</td>
<td>12%</td>
<td>12%</td>
</tr>
<tr>
<td></td>
<td>DIMOSIM</td>
<td>13%</td>
<td>5%</td>
<td>48%</td>
<td>16%</td>
</tr>
</tbody>
</table>

For the low horizon time, the comfort is not ensured as it is highlighted by the following graph:

**Figure 8: System profile for a horizon time of 2 hours**

As the usability is the indicator chosen for this study, there are a large majority of time steps where the value of usability is null (due to the low DHW demand). Thus, the system will react only if they is a DHW demand.

Considering higher values of horizon, the forecasting is wide enough to take into account the further DHW demand. The command is adapted in order to find the best compromise between comfort and energy consumption. Consequently, the usability rises at the expense of the backup consumption.

Hereafter a graph highlighting the behavior of the system for a horizon of 48 hours:

**Figure 9: System profile for a horizon time of 24 hours**

At first, we assumed that the higher horizon time is, the better the result are. However, it seems that once the horizon reached the length of the simulation, an efficiency downgrade appears. This can be explained by a data overflow, which leads to this kind of downgrade.

The following table summarizes the computation time for each horizon value:
Table 2: Variation of the computation time according to horizon

<table>
<thead>
<tr>
<th>Horizon</th>
<th>2h</th>
<th>4h</th>
<th>6h</th>
<th>8h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computing Time (hh:mm:ss)</td>
<td>01:45</td>
<td>02:14</td>
<td>03:23</td>
<td>04:45</td>
</tr>
<tr>
<td>12h</td>
<td>02:14</td>
<td>03:23</td>
<td>04:45</td>
<td></td>
</tr>
<tr>
<td>24h</td>
<td>03:23</td>
<td>04:45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>48h</td>
<td>04:45</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>72h</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Discussions

About the textbook study investigations

To go further on this textbook study, some fields of research would improve the MPC architecture. First, we can think about varying the alpha. Here, the choice was made to perform a Pareto front on one optimization overall the 3 days of study. However, it would be interesting to perform a Pareto front for each horizon. Indeed, there is a possibility of biased results coming from this settling of alpha value. We expect to find a best performance horizon at the same place, but this kind of study is necessary to alleviate doubts.

We would like to study the effect of a downgraded prediction on the efficiency. That is why we introduced the factor of availability. We expect that downgrading the prediction would lead to a loss of efficiency for an optimization based on usability at the benefits of an optimization based on availability. Indeed, the availability optimization seems to be more robust considering errors of prediction.

About the MPC architecture

Many investigations are possible around the MPC architecture, particularly regarding the sensitivity of the MPC.

It could be interesting to take advantages of the optimization model in the identification of unknown parameters and the state initialization. Indeed, by changing the objective function and the input of the optimization model, it would seem feasible to implement them into the MPC architecture.

The MPC architecture would need to be improved thanks to the implementation of a concrete orchestrator. Moreover, build a generic structure based on an oriented-object logic could enable to make the architecture more flexible.

Further perspectives

The mid-term objectives of this work are to test the orchestration of the MPC for more complex system is a key issue (Abreu et al., 2018). Choosing between a centralized or a decentralized strategy lead to different optimization model and orchestration. The aim is to build a proper case study that enables the implementation of those strategies:

In the end, we would like to test the implementation of the MPC architecture on the monitored zone (Mahendra et al., 2015) of the smart building GreEn’Er.

Conclusion

Urban policies are facing new environments on the energy field. More especially concerning the rising complexity of those systems. This article proposes a MPC architecture fitting with those new challenges. The developed MPC architecture has proven its efficiency of a textbook study. DIMOSIM platform has proven its efficiency as a good emulator and enables a perfect synchronization in order to ease the test of the MPC architecture. On the other hand, OMEG’Alpes has been a food solution for optimization and model construction. Once this test phase finalized, the implementation of future improvements would prove if it keeps its efficiency on complex systems at a district scale. Then, its implementation on a real system would enable to improve the orchestration of the MPC procedure, the robustness of the models and computation time.

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Reference


