Application on a residential building of predictive control based on a generic architecture of MPC modelling: focus on the identification of RC parameters

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RESUME. Ce papier présente le développement d'une architecture générique orientée-objet d'un MPC : contrôleur à base de modèles. En identifiant les composants principaux d'un MPC, nous développons différents outils pour la prédiction, l'estimation des paramètres ainsi que l'initialisation des variables d'état au sein de cette architecture. Un bâtiment résidentiel constitué d'une zone thermique est simulé à l'aide d'une plateforme de simulation nommé DIMOSIM, où sont intégrés les systèmes de chauffage. La stratégie de contrôle déterminée par le MPC doit assurer le confort thermique en période hivernal. On décrit ensuite le modèle de prédiction du bâtiment construit à l'aide d'un méta-modeleur de problèmes d'optimisation, OMEG'Alpes. Puis, l'orchestration permettant de déterminer la stratégie de supervision optimale est présentée ainsi que les outils de prédiction, d'estimation des paramètres et d'initialisation des variables d'état choisis. Enfin, les résultats de cette application sont mis en perspective en étudiant l'efficacité de la stratégie mise en place par le contrôleur.

MOTS-CLÉS : Système énergétique quartier, Simulation numérique, Contrôleur prédictif, architecture générique, échelle quartier, optimisation linéaire, pic de consommation

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ABSTRACT. All along this paper is presented the development of an oriented-object generic MPC architecture. After identifying the main components of an MPC, this architecture is developed taking into account the current and future integration of various tools for the prediction, estimation of parameters as well as the initialization of state variables. This paper presents the work in progress through a residential building composed of one thermal zone emulated into DIMOSIM, a district simulation platform. The associated heating systems are integrated. The control strategy consists in ensuring the thermal comfort during the winter period. Then, the paper describes the conception of the thermal building optimisation model using a linear optimization meta-modeller, called OMEG'Alpes. Then, the paper continues with the setup orchestration which determined the optimal supervision strategy and a description of the chosen prediction tool and the chosen parameter estimation and state variable initialiser tool. Finally, the paper discusses the results of this application and the effectiveness of such a supervision strategy.

KEYWORDS: Model Predictive Control, generic architecture, district scale simulation, linear optimisation, peak load

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1. INTRODUCTION

According to a European Union study, "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". With the up-coming climate change, the stakeholders in the building field are facing new challenges in order to reduce the impact on environment of building energy management at district scale.

Therefore, an evolution of the energy landscape is on-going: new actors appear as well as innovative storage devices (electric vehicles, Power to gas). This new environment lead research and development in the energy management field to develop new strategies at urban scale. Orthodox types of control of the district energy system, such as reactive control turn out to be less efficient in the near future.

That is one of the reason why the anticipative controller is more and more considered at district scale. This study describe an approach based on model based predictive control. Alongside this paper is presented an application of an anticipative controller based on the development of an oriented-object generic MPC architecture. This architecture needs to handle various methods and provide larger flexibility. It has been made to provide control strategy district scale. The specific components implemented for this are presented: the RC parameters estimator, the predictor and the prediction model. Through this case study, we test the efficiency of the tool in terms of control at a building scale and build the foundations of an effective platform at district scale.

2. IDENTIFICATION OF THE SPECIFIC COMPONENTS OF A MPC

2.1. THE SPECIFIC COMPONENTS OF A MPC

According to the literature, we could define a specific decomposition distinguishes five main components:

- The **predictor** consists in predicting the external conditions (Kiriakodis, 2019), related to weather conditions, and internal loads or gains, mainly related to the behavior of the occupants, (Darakdjan, 2018) for a considered district and its buildings. Three main archetypes can be cited: an external predictor tool, archetypes of day or training datasets
- The **estimator** consists in identifying the unknown parameters of a district model and can be sorted the same way the predictor is.
- The **state initializer** consists in initializing the state parameter of the system model.
- The **prediction model** is the representation of the system to be controlled in the MPC environment. For a given system, it is represented either using a white, grey or black box approach. The considered data for this model distinguish prediction data combining the external conditions and internal loads, the estimation data gathering the identified parameters of the system, the state variables, the control variables, the known parameters of the system.
- The **optimization model** is the combination of the prediction model, a set of constraint (physical or optimisation) and the objective function that are determined according to control purposes.
- The **solver** is used in order to solve the optimisation problem coming from the MPC procedure and provide the control strategy to be send to the district.

3. THE OBJECT-ORIENTED ARCHITECTURE TO BUILD GENERIC MPC AT DISTRICT SCALE

3.1. THE MAIN CLASSES OF THE ARCHITECTURE BASED ON THE MPC DECOMPOSITION

Figure 1 shows the object-oriented structure (Iwata, 2013) of the developed generic architecture for the MPC controller, built with « flexibility » as main aspect. This will allow the adaptation of the MPC controller to almost any district energy system.

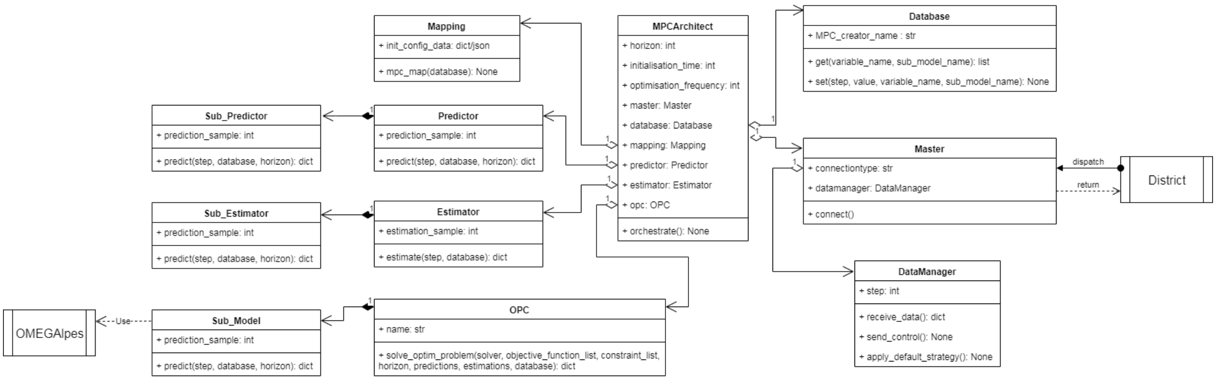

Figure 1 UML Graph of the oriented-object architecture

The main class of the architecture is the MPC Manager. It supports the configuration part of the MPC like the kind of Predictor instance, the kind of estimator instance and MPC parameters such as the prediction horizon, the optimization frequency and the estimation and prediction sampling time. The generic orchestration is processed using generic classes allowing the implementation of derivative classes designed for a specific use at district scale. The coupling between the controlled system and the MPC is made thanks to a Master class. A database class stores all the data relative to the MPC configuration as well as the measurements received by the controller. A mapping ensures the dispatching of the data stored in the database to the different tools ran during in the MPC orchestration process.

The orchestration of the MPC which provides the optimal control strategy is implemented through the MPC Manager. The algorithm launches sub-routines according to the corresponding class: receiving the measurements, launching the prediction procedure alongside the estimation and initialization procedure, preparing the optimization problem, solve it to determine the optimal control strategy, and send it to the controlled system.

3.2. A SUB-CLASSES PROCESS: MORE FLEXIBLE APPROACH

The derivative classes consist in a library of sub-classes. Those sub-classes are derivative classes from main classes: Predictor, Estimator and Model. They are combined to be implemented in the corresponding main classes.

The sub-classes are divided into:

- **Sub-model**: which are model of a part of the energy systems of the district. They are then assembled in order to get the prediction model of the whole district.
- **Sub-predictor**: predictor associated to a specific sub-model, (in order to provide for instance the future load profile for a specific zone, and the general exterior temperature, and solar radiation etc.)
- **Sub-estimator**: which consists in an estimation for specific parameters of the prediction model of the sub-model (such the resistance and capacitance for the RC model build for the thermal zone model).

The sub-class represent one system on its own, in this paper it's the thermal zone. But this can represent other energy systems integrated in energy networks. For instance, solar DHW or PV panel are represented with their own sub-classes. The objective here consists in developing a library that would provide the elements that build a model of the district. This application at building scale consists in a proof of concept of our choices in this architecture development.

4. BUILDING A ZONE MODEL: THE CORE OF THE THERMAL MODELLING AT DISTRICT

4.1. PRESENTATION OF THE CHOSEN MODEL: R3C2

In order to generate optimised control strategies allowing simple parameter estimation and high calculation speed, a reduced RC model (Figure 2) has been selected for the thermal zone modelling (Rouchier, 2018). The state formulation is shown in (1).

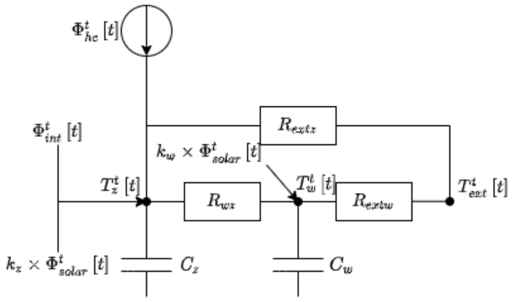

Figure 2 Scheme of the selected RC model

$$\frac{dT_z^t[t]}{dt} = \frac{T_w^t[t]-T_z^t[t]}{R_{wz}.C_z} + \frac{T_{ext}^t[t]-T_z^t[t]}{R_{extz}.C_z} + \frac{k_z}{C_z}.\Phi_{solar}^t[t] + \frac{\Phi_{hc}^t[t]+\Phi_{int}^t[t]}{C_z} \qquad \textbf{(1)}$$
$$\frac{dT_w^t[t]}{dt} = \frac{T_z^t[t]-T_w^t[t]}{R_{wz}.C_w} + \frac{T_{ext}^t[t]-T_w^t[t]}{R_{extw}.C_w} + \frac{k_w}{C_w}.\Phi_{solar}^t[t]$$

With:

- Tz and Tw respectively the indoor air temperature of the zone and the wall temperature,
- Text the outdoor temperature,
- Rwz, Rextz and Rextw the resistances of the RC model,
- Cz and Cw the thermal capacitors of the RC model,
- kz and kw the corresponding solar aperture of the RC model,
- Φ_{solar}^t the solar flux received by the thermal zone,
- Φ_{hc}^t the thermal flux from the thermal regulator,
- Φ_{int}^t the thermal flux from the internal gains.

Rextw includes heat exchange between the internal zone air temperature and the ambient via windows, thermal bridges, infiltration and ventilation.

4.2. MODEL BUILT ON A META-MODELLER OF OPTIMIZATION PROBLEM: OMEG'ALPES

OMEG'Alpes (Pajot, 2018) meta-modelling aspects allows to build the prediction model of the thermal zone as shown in Figure 3.

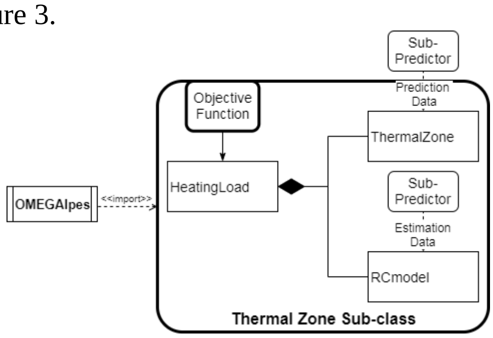

Figure 3 Model Structure based on OMEGAlpes

Hereafter we consider a detailed formulation of the optimisation problem corresponding to the thermal zone modelling. A binary variable count_under is implemented in order to assess the thermal comfort for this optimization problem. The state model equations are implemented as physical constraints using the meta-modeller.

Objective Function

$$\sum_{t=t_i}^{t_{end}} \alpha . \Phi_{hc}^{t}[t] + \sum_{t=t_i}^{t_{end}} (1-\alpha). count\_under^{t}[t] \quad \textbf{(2)}$$

Physical Constraints

$$283{,}15\text{ K} < T_z^t[t] < 313{,}15\text{ K},\ 253{,}15\text{ K} < T_w^t[t] < 323{,}15\text{ K} \quad \textbf{(3)}$$

$$T_z^t[t+1] - \frac{T_z^t[t]}{\mathrm{dt}} = \frac{T_w^t[t]-T_z^t[t]}{R_{w\_z}.C_z} + \frac{k_z[t]}{C_z}.\Phi_{sol}^t[t] + \frac{\Phi_{hc}^t[t]+\Phi_{int}^t[t]}{C_z} + \frac{T_{ext}^t[t]-T_z^t[t]}{R_{ext\_z}.C_z}$$

$$\frac{T_w^t[t+1]-T_w^t[t]}{\mathrm{dt}} = \frac{T_z^t[t]-T_w^t[t]}{R_{w\_z}.C_w} + \frac{T_{ext}^t[t]-T_w^t[t]}{R_{ext\_w}.C_w} + \frac{k_w[t]}{C_w}.\Phi_{sol}^t[t]$$

$$0 < \Phi_{hc}^t[t] < p_{hc,max}$$

Optimisation Constraints

$$(T_{max} - T_{comfort}) * (1 - count\_under[t]) * T_{comfort} > T_z[t] \quad \textbf{(4)}$$

$$(1 - count\_under[t]) * T_{comfort} < T_z[t]$$

Three sub-classes have been implemented to build the prediction model of the thermal zone. The heating load sub-class holds the thermal comfort objective function and represent the heating system in the thermal zone. The thermal zone sub-class represents the prediction data determined by the related sub-predictor integrating the state model equations of the thermal zone. The RCModel sub-class represents the estimated resistance and capacitance provided by the linked sub-estimator.

4.3. DESCRIPTION OF THE SUB-ESTIMATOR

Considering the thermal RC model, the key issue is to estimate correctly the RC parameters and to initialize the two state variables of the model. One option is to use a Kalman filter (Welch, 2006) and a stochastic representation of the model in order to get the resistance and capacitance according to the measurements provided by the district (a simulation platform in our case: DIMOSIM).

Figure 4 shows the estimation process for the proposed formulation. First, measurements values (the internal gains, the solar radiations, the external temperature, the zone temperature and the thermal output of the regulator) are provided to the Kalman filter. The thermal resistance and capacitance are determined by using a square-mean error method on the filtered model to calibrate the estimated known state variable to the measured one. Then an optimization problem is solved, to determine the solar aperture coefficient, using the prediction problem itself. At the same time, the initial wall temperature for the optimization problem is determined.

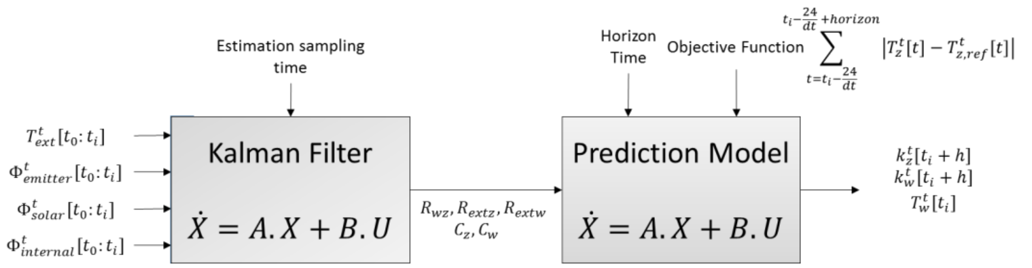

Figure 4 Sequencing of the sub-estimator module

4.4. DESCRIPTION OF THE SUB-PREDICTOR

Figure 5 depicts the sub-predictor for used in this application. It is based on a naïve prediction process. It consists in considering that the disturbances would be the same for the horizon time to come than the disturbances measured during the same period the day before.

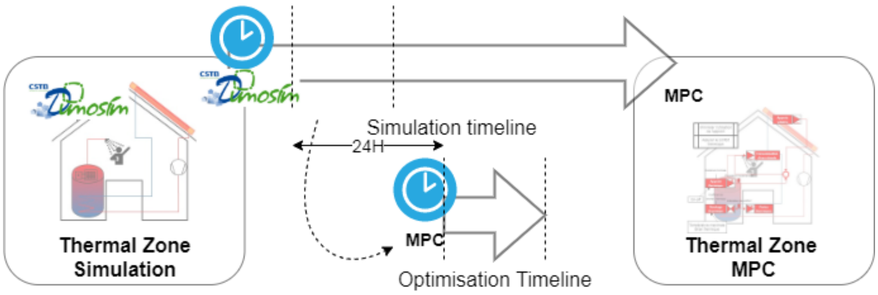

Figure 5 Sequencing of the sub-predictor module

4.5. ELABORATION OF THE SPECIFIC OPTIMIZATION PROBLEM

Figure 6 shows the set-up process during the run time that updates the optimization problem. Thus, DIMOSIM sends the measurements to the mapping instance. The database is updated considering these measurements which are distributed to the sub-estimator and the sub-predictor. The outputs of both modules are then provided to the prediction model, that form the optimization problem combined with a set of constraints and the objective function resulting the optimization problem. The optimization problem is then ready to be handled by the solver.

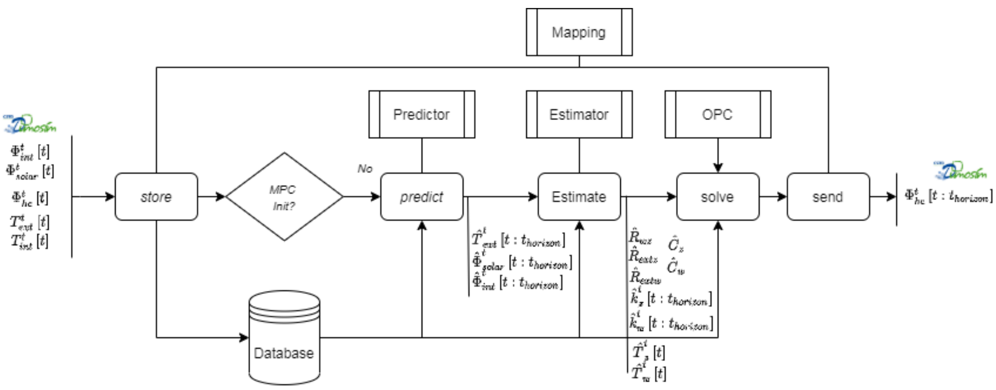

Figure 6 Elaboration scheme of the optimization model based on the sub-classes generation

4.6. RESULTS

The MPC controller has been applied to a mono-zone building from 12/28/2017 to 01/28/2018. A horizon of 24h, an estimation sampling time over 7 days, an optimization frequency of 6h and an initialization period over one week have been set for the MPC. This configuration means that the control strategy optimization would be effective after one week of simulation, once enough data have been stored; then the estimation would use a sampling of the 6 previous days measurements stored in the database, and the optimization would be run for 1 day. The last parameter, optimization frequency, means that the control strategy would be determined every 6 hours such as the identification of RC parameters.

In order to assess to robustness of the estimation process, we have chosen to see the impact of 3 different configurations (Table 1) of RC first guess initialization set. The initialization guess for the next estimations would be the estimations of RC parameters determined by the previous one.

The results of the coupling of MPC with the emulation provided by DIMOSIM are resumed in Table 2:

	Rwz K/W	Rextz K/W	Rextw K/W	Cw Wh/K	Cz Wh/K
Scenario 0	0,01	0,01	0,01	1,00E+07	1,00E+07
Scenario 1	0,0001	0,0001	0,0001	1,00E+08	1,00E+08
Scenario 2	0,1	0,1	0,1	1,00E+06	1,00E+06

Table 1 Scenarios of initialization of each resistance and capacitance

		Dimosim	Scenario 0	Scenario 1	Scenario 2
Thermal Consumption	Kwh	3095	3319	3216	3240
Thermal Comfort ratio		0%	1,4%	2,9%	0%
Computation Time	min	0,10	6,79	6,61	14,35

Table 2 Results from the coupling with the emulation

On the other hand, each estimation made during the simulation has been stored to see the evolution of the parameter during the process. Figure 7 and Figure 8 show the boxplot of the estimation dataset for each predefined scenario.

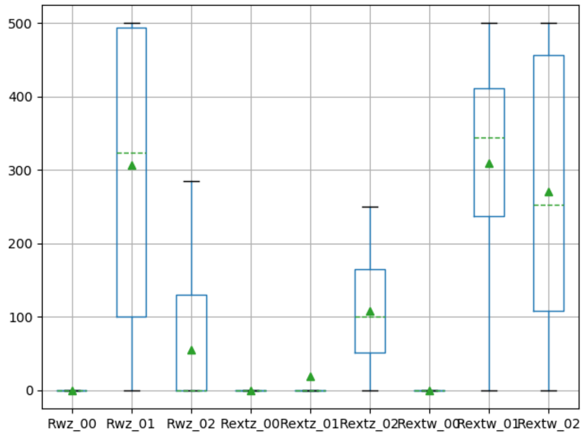

Figure 7 Boxplot of resistances for each scenario

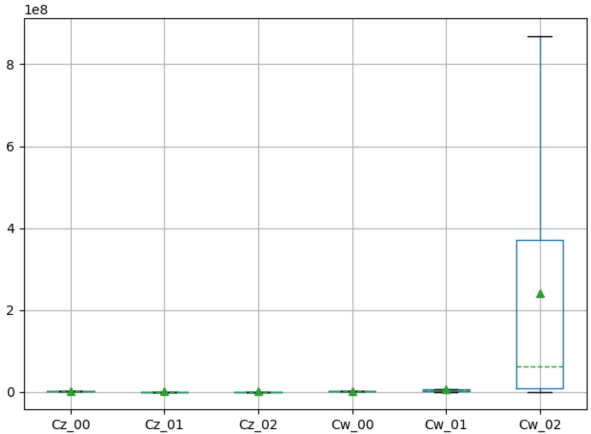

Figure 8 Boxplot of resistances for each scenario

This study validates the coupling's functioning between the MPC and its emulation as well as the orchestration of the MPC. However, we can assume that the result of the coupling is deeply dependent to the initialization of the estimation Kalman Filter for RC model parameters. This is a problem that has been tackled in previous works such as in (Le Mounier 2013).

4.7. PERSPECTIVES

The first implementation that can be engaged consists in scattering the RC model parameters to investigate which parameter is sensitive or not (Nguyen, 2017). That has been done leading to the development of an estimation procedure based on a combination of Morris and Sobol analysis method. This application has been redesigned implementing this procedure, resulting a study of the performances of the control strategy determined by the MPC. Three variation of the thermal zone model has been developed and tested. Hereafter a table that store the energy savings from the anticipative control strategy:

	Perfect Predictor	Naive Predictor	Rule-based Predictor
Office	15-16%	13-14%	15%
Residential	9-10%	9%	7-8%

Table 3 Energy savings comparison of reactive control and anticipative control for two different buildings

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