Optimal control of a multi-energy district boiler: a case study ⋆

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Abstract: The present paper deals with the optimization of a multi-energy district boiler (La Rochelle, France) which supplies domestic hot water and heats residential and public buildings, using renewable and fossil resources. First, a combination of white, grey and black boxes was used to model the plant, thanks to a modular approach. Next, a stratified thermal storage tank was modelled and completed the just-mentioned plant model. Using these models and forecasted sequences about outdoor temperature and thermal power consumption, a model predictive controller allows optimizing the use of both the tank and the wood boiler. As a result, fossil energy consumption and CO_2 emissions are minimized. Energy is stored during low-demand periods and used when demand is high, instead of consuming gas and fuel oil.

Keywords: Modelling, Identification, Prediction, Neural networks, Predictive control, Boiler, Energy storage, Renewable energy systems.

1. INTRODUCTION

By the end of the first commitment period of the Kyoto Protocol in 2012, the European Union has decided for 2020 to promote renewable energy (EU (2009b)) (20 %), to reduce GreenHouse Gases (GHG) emissions (EU (2009a)) (−20 %) and to increase energy efficiency (+20 %). As part of the OptiEnR research project (Eynard (2010)), the present paper deals with optimizing a multi-energy district boiler, situated at La Rochelle (west coast of France) and managed by Cofely GDF-Suez. The plant supplies domestic hot water and heats residential and public buildings. It is described in section 2 and uses renewable (wood) and fossil energies (gas and fuel oil). The main objective of the project was optimizing the district boiler functioning while minimizing the consumption of fossil energy. This has been completed according to 4 successive tasks (Fig. 1). The first task (section 3) was to model the district boiler. Because of both the complexity of the plant as a whole and the strong interactions between the sub-systems, a modular approach was proposed. To carry out that task, measurements campaigns results as well as several modelling approaches, such as black-box, parametric or knowledge modelling approaches, were considered. Because energy storage is a way to optimize the performance of a district boiler, we studied the impact of adding a stratified hot water tank to the plant of La Rochelle (section 4). Next, a Model-based Predictive Controller (MPC) was designed to optimize both the flow of the water passing through the tank and the wood boiler set-point temperature (section 6) minimizing a cost function based on fuel oil consumption. The controller uses the developed overall model and forecasted outdoor temperature and thermal power consumption sequences (section 5). Section 6 focuses on the way the MPC was tuned and on simulation results. One

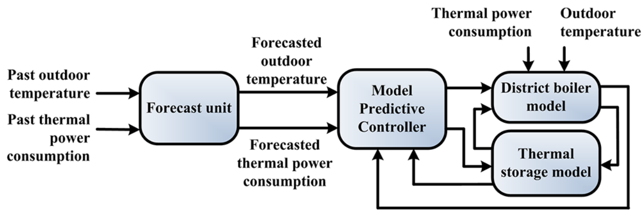

Fig. 1. The OptiEnR research project

can highlight a significant decrease of the fossil energy consumed, leading to a reduction in costs and CO_2 emissions.

2. DISTRICT BOILER OF LA ROCHELLE

The district boiler of La Rochelle is a complex plant (Fig. 2). The collecting hydraulic circuit connects the wood (4.5 MWh) and the gas-fuel oil (7 MWh) boilers, using two feed pumps (Fp_{WB} and Fp_{GFB}). Due to the low price of wood, the wood boiler functions all the time while the gas-fuel oil boiler is used during very cold periods only, when the wood boiler fails to respond to the hot water demand. First, the gas-fuel oil boiler is fed using gas. When the 6000 m^3 of gas allowed every day to Cofely GDF-Suez are consumed and if the boiler must continue to run, fuel oil is used until the end of the day (in this case, gas is much more expensive than fuel oil). The primary hydraulic circuit (3000 m^3) supplies hot water to heat residential and public buildings, for a total of 2700 accommodations. Domestic hot water is also produced, for a total of 3500 accomodations. The circuit is composed of a hot water distribution network, a feed pump (Fp_{DN}) used to control the network differential pressure, and a cogeneration plant which produces electricity. A part of the cold water coming back from the distribution network is warmed up by the cogeneration plant. Using measurements of both the

⋆ Industrial partner: Cofely GDF-Suez

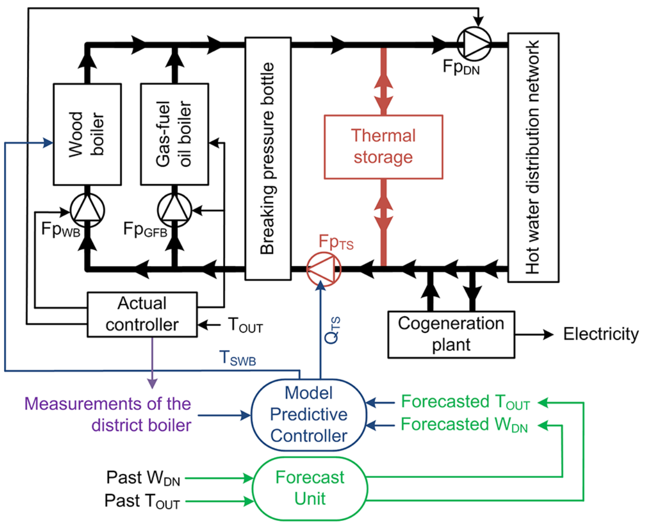

Fig. 2. Synopsys of the district boiler with the proposed modifications (in red, green, blue and purple)

outdoor temperature and the temperature of the water entering the distribution network, a monitoring system allows tracking the functioning of the two boilers. Finally, the breaking pressure bottle pulls apart the two just-mentioned hydraulic circuits, because of the difference between their respective flows.

3. DISTRICT BOILER MODELLING

3.1 Overall approach

Taking a look at the state of the art about the modelling of district boilers, one can highlight some interesting works. First, Curti et al. (2000) proposed an environomic approach for modelling and optimizing a district heating network. Dias and Balestieri (2004) modelled a wood boiler using a detailed energy and exergy analysis, allowing quantifying the types, causes, and locations of losses. Physical principles and artificial neural networks can be used together as it has been shown by Lu and Hogg (2000) for the development of a nonlinear power plant model. Finally, Ghaffari et al. (2007) presented a soft computing approach to model electrical power generating plants and to characterize the essential dynamic behavior of the plant sub-systems. Their approach consisted of fuzzy logic, artificial neural networks and genetic algorithms. As previously mentioned and because of both the complexity of the district boiler of La Rochelle as a whole and the strong interactions between the sub-systems, a modular approach was proposed to model the plant (Eynard et al. (2011a)). According to the availability of information (as a result of measurement campaigns or taking into consideration expert knowledge about the sub-systems functioning and the boilers control systems), a combination of white, grey and black boxes was used to keep the modeling process on track. With white boxes which can be used when one can easily describe the interactions between physical parameters, experimental data serve only to validate the models. Both grey boxes (Sjöberg et al. (1995)) (in this case, one needs to find appropriate model inputs and outputs, thanks to physical considerations and/or analyzing the process dynamic properties, while experimental data

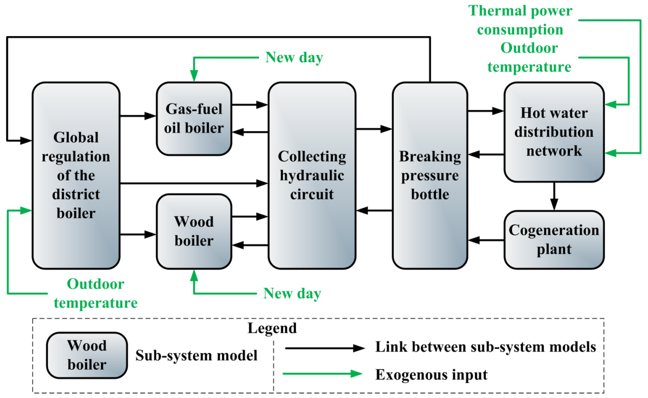

Fig. 3. Modular approach to model the district boiler

are used to optimize both the model topology and parameters (Ljung and Ljung (1987)) as well as validation data) and black boxes (in this case, no physical considerations are taken into account, a standard topology is used and, as when using grey boxes, one needs to find appropriate model inputs and outputs and to optimize, with experimental data, the model parameters) are used in case of missing information about physical behaviours.

3.2 Modelling process

First, a data processing phase allowed eliminating abnormal data and upsampling data with a too-high sampling rate, considering a desired sampling rate of 5 minutes. Let us also note that some relevant but not-measured parameters were estimated thanks to appropriate information. Next, for each parameter to be modelled, both the model topology (a differential, algebraic or logical equation) and inputs were defined. A first iterative process of optimisation was performed to identify the coefficents of the models. We used the trust-region reflective Newton method (Coleman and Li (1994)) for nonlinear least-squares (Kelley (1999)) to solve the minimization problem. Analyzing the results allows validating the chosen topologies (if a result is not satisfactory, one needs to think about another model topology and of course to find the right equation coefficients again). With the boiler parameters correctly described, using optimized differential, algebraic or logical equations, sub-models were defined. It can be noticed that the black-box methodology used for the modelling of the wood boiler was based on the Hammerstein-Wiener theory (Zhu (2002)). A second iterative process of optimisation was carried out to adjust the sub-models coefficients. Finally, when the sub-models accuracy was as good as possible, these models were combined to obtain the overall district boiler model. Fig. 3 depicts the modular approach, leading to very good results.

4. ENERGY STORAGE MODELLING

4.1 Hypothesis

Adding to the district boiler of La Rochelle an energy storage unit allows using, when demand is high, the excess of energy produced by the wood boiler during low-demand periods, instead of consuming gas and fuel oil. As a result, the coverage rate of the fossil energy used can be significantly reduced thanks to a better exploitation of the available renewable resources. Many options about the materials one can use to store energy were considered but due to technical reasons, their cost, the constraints related to their integration into the district boiler, their toxicity, their flammability or their relative low power, phase change materials were not used. So, we decided for a hot water tank. Some hypothesis about its shape, size and position were made. We proposed a vertical cylindrical tank whose diameter is equal to its height with the aim of minimizing its surface and, as a consequence, thermal losses. For the same reason, we supposed the tank, whose thermal insulation is insured by 10 cm of polypropylene, to be buried in the ground, where ambiant temperature (T^{amb}) is about 10 °C. The inlet fluid temperature (T^{in}) affects the first layers of water in the tank only, because of a grid used to protect its thermal stratification.

4.2 Modelling results

After taking a look at the review of Han et al. (2009) dedicated to the modelling of one-dimension hot water tanks, i.e. with vertical thermal stratification, we developed a discrete space model. The model is adapted from the model proposed by Alizadeh (1999) and defined by equations (1) and (2) for energy storage and destocking. $T_{i,k}$ is the temperature of the i^{th} layer of water at time index k, g is the number of layers, e is the number of layers directly affected by the inlet fluid temperature, V is the volume of one layer of water while ΔV is the volume of fluid passing through the tank during one sampling time.

$$\begin{cases} (i > g-e): \ T_{i,k+1} = \frac{(V-(\frac{\Delta V}{e}))\cdot T_{i,k}+(\frac{\Delta V}{e})\cdot T_k^{in}+\beta_i\cdot T_k^{amb}}{\alpha_i} \\ (i \leq g-e): \ T_{i,k+1} = \frac{(V-\Delta V)\cdot T_{i,k}+\Delta V\cdot T_{i+1}(k)+\beta_i\cdot T_k^{amb}}{\alpha_i} \end{cases} \quad (1)$$

$$\begin{cases} (i \leq e): \ T_{i,k+1} = \frac{(V-(\frac{\Delta V}{e}))\cdot T_{i,k}+(\frac{\Delta V}{e})\cdot T_k^{in}+\beta_i\cdot T_k^{amb}}{\alpha_i} \\ (i > e): \ T_{i,k+1} = \frac{(V-\Delta V)\cdot T_{i,k}+\Delta V\cdot T_{i-1,k}+\beta_i\cdot T_k^{amb}}{\alpha_i} \end{cases} \quad (2)$$

4.3 Integration of the storage unit into the district boiler

The characteristics of the thermal storage unit being defined, one may think about the way the tank would be integrated into the district boiler. That is why we proposed an hydraulic modification of the plant, as shown in red on Fig. 2. We decided to place the tank between the breaking pressure bottle and the hot water distribution network, before the feed pump of the distribution network and after the cogeneration plant. A new pump (Fp_{TS}) is used to control the flow of the water passing through the tank. To reflect the impact of the thermal storage unit on the district boiler, some subsidiary models were developed, as shown by Fig. 4. Indeed, some flows between the breaking pressure bottle and the thermal storage tank changed while some temperatures were affected by the tank functioning.

5. EXOGENOUS VARIABLES FORECASTING

5.1 Materials and methods

Both the outdoor temperature (T_{out}) and the thermal power consumption of the hot water distribution network

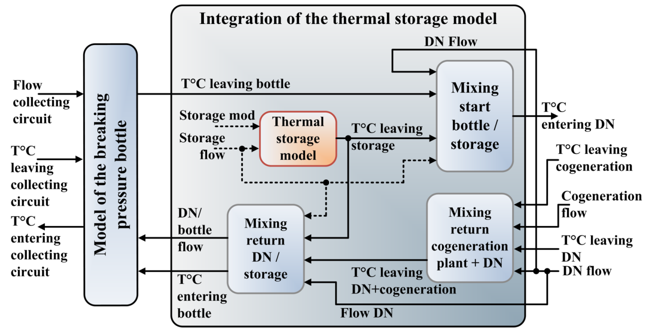

Fig. 4. Integration of the model of the thermal storage unit

(W_{DN}) are the district boiler model inputs. One needs, using the model, forecasted sequences about these two exogenous parameters to optimize on-line the use of the thermal storage tank. During the last years, schemes for temperature forecasting were mainly developed in the context of load forecasting and power utilities management. The complex and nonlinear nature of temperature variations as well as the abundance of historical data suggest that computational intelligence data-based modeling techniques would be good candidates to forecast temperature (Neto and Fiorelli (2008)). The proposed methodology, adapted from the methodology developed by Tran et al. (2008), deals with the concept of time series, even if not only past values are considered for estimating future values, and uses a wavelet-based Multi-Resolution Analysis (MRA) and Artificial Neural Networks (ANN). One could speak of "MRA-ANN" methodology, described in detail in Eynard et al. (2011b). The discrete wavelet transform allowed decomposing M sequences of past data (of l points) in subsequences, according to different frequency domains. We used a filter bank, composed of low-pass and high-pass filters, to obtain approximation (i.e. low frequency components) and detail (i.e. high frequency components) coefficients, according to a decomposition level (N) and a wavelet order (R) (Fig. 5). From these coefficients, Multi-Layer Perceptrons (MLP) were used to estimate future subsequences of 4h30. As depicted by Fig. 6, $N+1$ neural networks were used to estimate the N details and the approximation of level N of a target sequence P (the sequence to be forecasted). Future values of outdoor temperature or thermal power consumption were then obtained by simply summing up the estimated coefficients (Fig. 6). Substituting the prediction task of an original time series of high variability by the prediction, using MLP neural networks, of its wavelet coefficients on different levels of lower variability, is the main idea of the methodology. The wavelet-based multi-resolution analysis allowed isolating the global trend and the 24-hour pseudo-period characterizing the considered time series from the variability caused by climatic phenomena. To place the model in time, the sequences of past data were completed, for each of their components, by the minute of the day and the day of the year. According to the respective values of M, l and of the sub-sampling time T_{SST} (set initially to 30 minutes; forecasted sequences were then upsampled to be in agreement with the sampling time of all the parameters measured at the district boiler), the results can be more or less accurate. Indeed, the further the forecasting horizon (set to 4h30, as requested by the boiler operators; this leads to l=9), the more inaccurate it can be. Inaccuracy

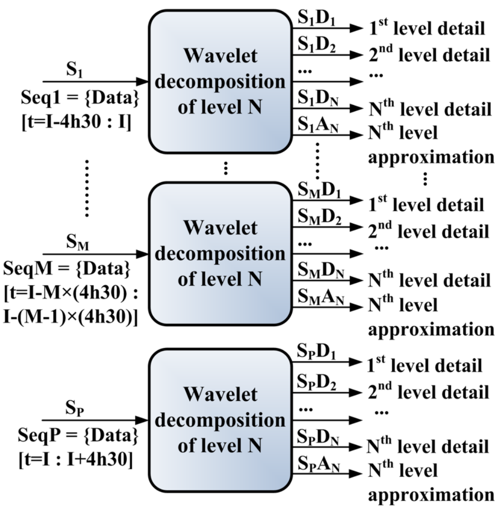

Fig. 5. Wavelet-based multi-resolution analysis

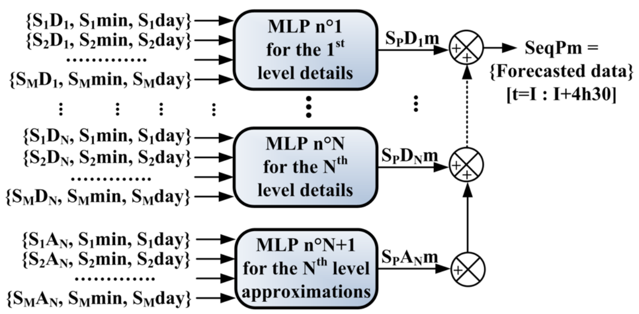

Fig. 6. Forecasting of future sequences using ANN

can also be the result of a lack of usable information provided by past sequences and/or a too low number M of considered past sequences (examples to be learned and used to forecast future values of the considered parameters). The proposed neural model was developed using half of the available sequences and validated thanks to the remaining sequences. The particularities of the proposed MRA-ANN methodology lies in the use of sequences, in the addition of temporal information allowing a better understanding of how the considered parameters (T_{out} and W_{DN}) evolve in time, and in the use of a specific neural network for estimating one of the wavelet coefficients of the future values we want to forecast.

5.2 T_{out} and W_{DN} forecasting results

Table 1 depicts the optimal configuration used to forecast T_{out} and W_{DN} (the parameters are inversely proportionnal), according to the wavelet order (R), the wavelet decomposition level (N), the common topology of the networks used (F), the number of considered past sequences (M) and, finally, the sub-sampling time used (T_{SST}). Table 2 (lines 1 and 2) specifies, for the considered period (from February 15, 2009 to March 02, 2009), the Mean Relative Error (MRE), the Mean Absolute Error (MAE) and the curve fitting (FIT) observed when forecasting T_{out} and W_{DN}, using the MRA-ANN methodology. Table 2 (line 3) also presents the results obtained when using T_{out} to forecast W_{DN}, via a simple linear curve fitting. Finally, a hybrid approach, combining the MRA-ANN methodology and linear curve fitting (Table 2 (line 4)), was used to forecast W_{DN}. Although the proposed methodology provided better results than linear curve fitting, it underestimated sometimes peaks of consumption. Both approaches are valid but have different characteristics. That is why they were used in tandem to improve the forecasts accuracy.

Table 1. Optimal configuration

Parameter	Symbol	Optimal value
Wavelet order	R	4
Wavelet decomposition level	N	5
Common number of hidden neurons	F	5
Number of past sequences	M	4
Sub-sampling time	T_{SST}	30 mn

Table 2. T_{out} and W_{DN} forecasting results

Variable	FIT	MRE	MAE
T_{out}^{4H30}	60.6 %	4.14 %	1.15 °C
W_{DN}^{4H30}	44.7 %	6.07 %	663.6 kW
$W_{DN}^{T_{out}^{4H30}}$	38.4 %	6.94 %	758.3 kW
W_{DN}^{hyb}	46.9 %	5.85 %	639.1 kW

6. OPTIMAL CONTROL OF THE DISTRICT BOILER

6.1 Control strategies

First, some criteria to be minimized were developed and used to optimize the performance of the district boiler. Equations (3-8) define J_1 as the cost related with fuel oil consumption, J_2 as the positive difference between the temperature of the water entering the distribution network (T_{DN}^{E}) and the temperature setpoint (T_{SDN}), J_3 as the energy consumed (in LHV), J_4 as the fossil energy coverage rate, J_5 as the level of CO_2 emissions and J_6 as the overall performance of the district boiler with a controlled thermal storage unit compared with its performance without energy storage. Table 3 presents the Unitary Cost (UC), the Unitary Low Heating Value ($ULHV$) and the Unitary CO_2 emissions in Life-Cycle Assessment ($ULCA$) for each of the fuels used (ADEME (2007)). Let us note that we used for wood the number of tappet strokes per five minutes (the mean weight of the wood introduced into the boiler by the tappet is about 37 kg).

$$\begin{aligned} J_1 = & \, UC_{wood} \cdot N_{tappet} + UC_{gas} \cdot V_{gas} \\ & + UC_{fuel\text{-}oil} \cdot V_{fuel\text{-}oil} \end{aligned} \tag{3}$$

$$J_2 = \frac{1}{2 \cdot N} \cdot \sum_{k=1}^{N} \left(\begin{array}{c} \left|T_{SDN}(k) - T_{DN}^{E}(k)\right| \\ - \left(T_{DN}^{E}(k) - T_{SDN}(k)\right) \end{array} \right) \tag{4}$$

$$\begin{aligned} J_3 = & \, ULHV_{wood} \cdot N_{tappet} + ULHV_{gas} \cdot V_{gas} \\ & + ULHV_{fuel\text{-}oil} \cdot V_{fuel\text{-}oil} \end{aligned} \tag{5}$$

$$J_4 = \frac{ULHV_{gas} \cdot V_{gas} + ULHV_{fuel\text{-}oil} \cdot V_{fuel\text{-}oil}}{J_3} \tag{6}$$

$$\begin{aligned} J_5 = & \, ULCA_{wood} \cdot N_{tappet} + ULCA_{gas} \cdot V_{gas} \\ & + ULCA_{fuel\text{-}oil} \cdot V_{fuel\text{-}oil} \end{aligned} \tag{7}$$

$$J_6 = \frac{1}{5} \cdot \sum_{n=1}^{5} \left(100 \cdot \frac{J_n(\text{with thermal storage})}{J_n(\text{without thermal storage})} \right) \tag{8}$$

Minimizing one of the just-mentioned criteria defines the control strategy used for optimizing the district boiler performance. According to economic, technical, environmental or related-to-energy-efficiency considerations, one can choose one of the first five criteria we proposed. With the criterion J_6, one can optimize the district boiler performance in an unspecific way, according to all the just-mentioned considerations.

6.2 Model-based optimal predictive controller

The model predictive controller developed to optimize the district boiler performance uses the models of both the plant and the thermal storage unit as well as forecasted sequences of T_{out} (the outdoor temperature) and W_{DN} (the thermal power consumption of the hot water distribution network). It computes optimal command sequences to be applied to the considered process over a prediction horizon, according to an objective function to be minimzed. Taking a look at the literature, one can note that through MPC is not inherently more or less robust than classical feedback, it can be adjusted more easily for robustness (García et al. (1989)). Moreover, it has good properties of stability (Mayne and Schroeder (1997)) and can be used to control nonlinear systems (Kambhampati et al. (2000)), hybrid systems (Olaru et al. (2008)) or even fast systems (Pannocchia et al. (2007)). Such a controller is commonly used to control industrial processes in real-time (Qin and Badgwell (2003)). The wood boiler set-point temperature (T_{SWB}) and the flow of the water passing through the hot water tank (Q_{TS}) are the two controlled parameters (Fig. 2). Let us note that information related to measured data is given to the MPC by the previously-implemented control schemes. Equation (9) shows the command vectors to be applied to the process and to be optimized thanks to the minimization of the chosen criterion J_1. Equation (10) defines the path constraints, with p and c the prediction and control horizons, respectively. The thermal storage unit can not store hot water when the gas-fuel oil boiler is engaged ($Eng_{GFB} = 1$) while thermal stratification must always be ensured. As a consequence, the temperature of the water leaving the breaking pressure bottle (T^L_{BPB}) has to be higher than the temperature of the upper layer of the tank (T_{sup-TS}). The resolution of the nonlinear optimization problem was carried out using a pattern search algorithm (Sherif and Boice (1994)). Such a global optimization method is well adapted for nonlinear problems with unknown gradient fonctions. It is commonly used for the resolution of complex industrial problems, for example a constrained optimization problem in a way that insures a secure-economic system operation (Al-Othman and El-Naggar (2008)).

$$\begin{bmatrix} Q_{TS}(k/k), \ldots, Q_{TS}(k+c-1/k) \\ T_{SWB}(k/k), \ldots, T_{SWB}(k+c-1/k) \end{bmatrix} \tag{9}$$

Table 3. Characteristics of the fuels used

	Wood [−]	Gas $[\mathrm{m}^3]$	Fuel oil [l]
UC [€]	1.8648	0.378	0.40
$ULHV$ [kW·h]	133.2	10.5	9.76
$ULCA$ [kgCO_2]	1.7316	2.283 84	2.928

$$\begin{cases} \text{Overall district boiler with thermal storage} \\ \text{model whose inputs are } T_{out}^{4h30} \text{ and } W_{DN}^{hyb} \\ |Q_{TS}| \leq Q_{DN} - 10 \\ (Eng_{GFB} = 1) \vee (T^L_{BPB} \leq T_{sup-TS}) \Rightarrow Q_{TS} \leq 0 \\ 90\,^\circ\mathrm{C} \leq T_{SWB} \leq 97\,^\circ\mathrm{C} \\ \Delta Q_{TS}(k+h) = 0 \ \forall h \in [\![c; p-1]\!] \\ \Delta T_{SWB}(k+h) = 0 \ \forall h \in [\![c; p-1]\!] \\ (p, c) = (54, 36) \end{cases} \tag{10}$$

6.3 Optimal predictive control results

The proposed controller was tested in simulation during 45 days, from mid-January to early March. We focused on the impact of the hot water tank volume (V_{tot}), ranging between $500\,\mathrm{m}^3$ and $4000\,\mathrm{m}^3$. Table 4 highlights three remarkable configurations for the proposed control scheme (MPC_1, MPC_2 and MPC_3 defined according to three different tank volumes and allowing minimizing J_1), taking as a reference the modelled functionning of the district boiler without thermal storage unit and MPC controller.

Table 4. Remarkable configurations

Criteria		Configurations			
Name	Unit	Reference	MPC_1	MPC_2	MPC_3
V_{tot}	m^3	0	1000	1500	4000
N_{tappet}	-	24 635	21 260	21 203	21 482
V_{gas}	m^3	38 001	17 553	17 533	17 207
V_{fuel}	l	3287	2043	2244	2436
J_1	k€	61.62	47.10	47.07	47.54
J_2	°C	0.56	0.247	0.252	0.272
J_3	MW·h	3712	3036	3030	3066
J_4	%	11.6	6.73	6.80	6.67
J_5	tCO_2	139.1	82.9	83.3	83.6
J_6	%	100	64.0	64.3	65.2

Taking a look at Table 4, one can note that configuration MPC_1 reduces the fuel oil consumption by 37 % (−1244 l), the set-point tracking error (J_2) by 55 % (−0.313 °C), the CO_2 emissions (J_5) by 40 % (−56.2 tCO_2), and the performance criterion J_6 by 36 %. With configuration MPC_2, the wood consumption, the economic cost (J_1) and the primary energy used are reduced by 14 %, 24 % (−14.55 k€) and 18 % (−682 MW·h), respectively. Finally, configuration MPC_3 minimizes the gas consumption by 55 % (−20 794 m^3) as well as the fossil energy coverage rate (J_4) by 42.5 % (−4.93 points).

7. CONCLUSION

The present paper deals with optimizing the performance of a multi-energy district boiler which supplies hot water via a distribution network. First, black, grey and white boxes were used to model the considered process, according to a modular approach. Such an approach was the consequence of both the complexity of the plant as a whole and the strong interactions between the subsystems. Next, a stratified hot water tank, connected to the primary circuit, was modelled and completed the district boiler model. Because one needs, using the overall model proposed, forecasted sequences of both the outdoor temperature and the thermal power consumption of the distribution network (both parameters are the overall model inputs) to optimize the use of the tank on-line, a prediction tool was also developed. It is based on a multi-resolution analysis and artificial neural networks. Finally, a model predictive controller was developed to optimize, over a prediction horizon, the use of both the thermal storage unit and the wood boiler. It uses the overall model and the just-mentioned forecasted sequences. One can highlight that the proposed control scheme allows reducing the fossil energy consumption significantly and, as a result, functioning costs and CO_2 emissions. Future work will focus on improving both the district boiler model and the storage process, using phase change materials as well as another way to implement the hot water tank. One can also think about alternative control schemes, such as fuzzy or neural control schemes, before implementing in-situ the developed tools.

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