DISTRHEAT

Digital intelligent and scalable control for renewables in heating networks

Deliverable D2.3

Description of the Model Predictive Control algorithm, including concept, block diagram, implementation and software specifications

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Executive summary

The deliverable summarizes the results from task “T2.3 Model Predictive Control algorithm develpment”, the goal of which was to develop an innovative control strategy for multi-energy systems feeding district heating and cooling networks based on Model Predictive Control (MPC).

The proposed algorithm aims to combine the benefits of short-term optimization (i.e. with short control horizon and high detail) and long-term optimization (i.e. with long control horizon and low time resolution) within a unique architecture, that is able to (i) fulfill end-user demand of all energy vectors, (ii) couple two different time scales, and (iii) be applied in a real-time MPC.

The three interacting space and time control layers of the control architecture are:

- Distribution modules, for controlling the energy distribution to a section of the heating and cooling network
- **Short-Term Supervisory module**, namely **ShoTS**, a low-level supervisory controller which controls the thermal power station in real time, based on a short-term objective and prediction horizon.
- **Long-Term Supervisory module**, namely **LoTS**, a high-level supervisory controller which solves the yearly scheduling problem of the thermal power station with a daily time resolution, including long-term factors. It also generates optimal bands of operation for the variables of the ShoTS problem (i.e. long-term constraints).

In the long run, real-time automatic control carried out by ShoTS should lead to the fulfillment of the yearly goals, since it is forced to follow the optimal bands of operation given by LoTS. These modules are Model Predictive Control agents and, hence, their calculations are repeated every time-step in order to provide an updated solution every time new information is available.

The **LoTS module** solves an energy scheduling problem with reference to the energy produced daily by the energy conversion units in the thermal power station. Its objective is to define the daily energy production over the entire year to minimize the total operating cost (including the revenues from incentives such as the Energy Efficiency Titles for high efficiency cogeneration). The problem is a Linear Programming with the following sets of constraints: daily demands to be satisfied, operational boundaries, maximum and minimum variable constraints (for defining optimal bands of operation), contractual/yearly constraints, seasonal storage, and maximum operating hours of the plants.

The **ShoTS module** solves a highly detailed unit commitment problem. Its objective is to define the operation of the energy conversion units in the thermal power station in order to minimize the operating cost over a short-term prediction horizon. The problem is a Mixed Integer Linear Programming with the following sets of constraints: demands to be satisfied, operational boundaries, ramp constraints, long-term constraints (from LoTS), start-up costs, hierarchical constraints (to avoid problem symmetry), minimum up-time and down-time, and maximum number of start-ups in the prediction horizon.

The software implementation has been done in MATLAB® for the simulation and testing in the Model-in-the-Loop environment and in Python for the demonstration in the real test site. The entire procedure is carried on automatically by means of a scheduler. The ShoTS and LoTS parameters are declared in .json files, the disturbances and real system operation of the Cona Hospital are passed through .csv files, and the output of the control logic is returned within a .csv file, which is read by the Building Energy Management System to apply the control action.

1. Introduction

This report is the deliverable D2.3. of work package WP2 of the DISTRHEAT project, led by University of Parma. The work package "WP2 – System study, modeling and algorithm development for small DHC" aims to develop a system model of a small-scale District Heating and Cooling network (DHC), in particular of the small-scale case study, and an optimization algorithm suitable for its optimal management within a Model Predictive Controller.
The coordinated activities of WP2 are illustrated in Figure 1.

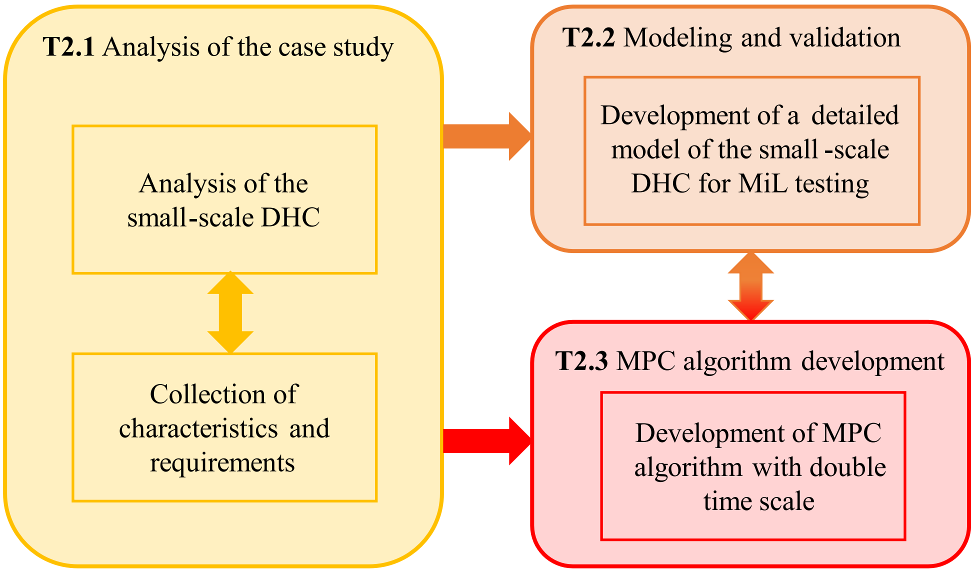

Figure 1. Schematic representation of main tasks and activities of WP2. The present deliverable focuses on T2.3.

The deliverable summarizes the results from task "T2.3 Model Predictive Control algorithm develpment", the goal of which was to develop an innovative control strategy for multi-energy systems feeding district heating and cooling networks based on Model Predictive Control (MPC). The strategy should have a double-time scale hierarchical configuration, with different interacting control levels, which have the scope to combine real-time control (possible only in the short-term) with long-term objectives and constraints typical of yearly scheduling approaches. Indeed, the control module on the higher level optimizes the constraints for the low level control module on a yearly basis, by accounting for economic aspects and incentives. In turn, the low level module optimally controls the system based on a daily objective function. The controller has to be customized for the implementation to the small DHC network studied and analyzed in T2.1.
In this deliverable, the control architecture and objectives are firstly determined. Secondly, the two supervisory control levels are developed and described separately. Then, the communication between the control levels, implementation and software specifications are reported. The control strategy outlined in this deliverable can be tested and verified in the Model-in-the-Loop simulation environment of T2.3, or it can be implemented in the real test site, as an activity of WP3.
The work has been conducted from M13 to M24 of the project.

2. Control algorithm architecture

2.1. General concept

The state-of-the-art optimization algorithms for energy systems available in the literature focus either on short-term optimization (i.e. with short control horizon and high detail) or on long-term optimization (i.e. with long control horizon and low time resolution). The proposed algorithm aims to combine the benefits of these two approached within a unique architecture, that is able to manage integrated energy networks with multiple interacting energy vectors and required energy services, as well as several energy conversion plants to be coordinated in the thermal power station.
The control algorithm has the following goals and features (Saletti et al., 2022):

- Fulfillment of end-user demand of all energy vectors (e.g. heating, cooling, electricity, and steam) with the lowest operating cost on a yearly basis, including the revenues deriving from incentives (e.g. Energy Efficiency Titles for high efficiency cogeneration);
- Coupling of two communicating optimization layers which operate at two different time scales, i.e. long-term optimization coupled with short-term optimization.
- Modular and suitable in particular to small-scale district energy, e.g. campus, hospitals (as the case study presented in D2.1), and small neighborhoods.
- Application in a real-time controller based on Model Predictive Control. Since this requires the algorithm to be updated and recalculated at each time interval, a high computational speed that enables real-time control applicability is of primary importance.

The original concept and all its layers are illustrated in Figure 2.

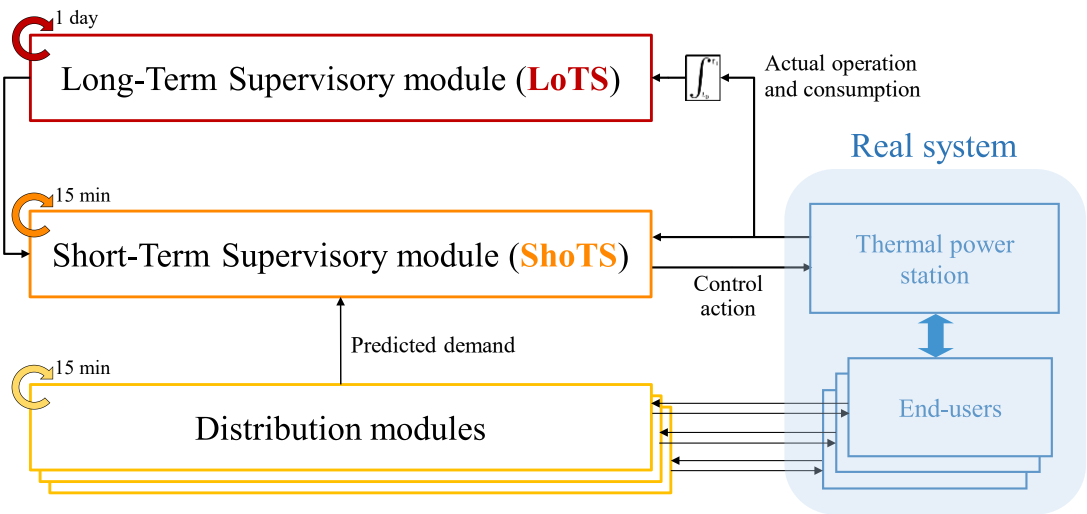

Figure 2. Block diagram of the Model Predictive Control algorithm developed in the project. It is possible to recognize the two supervisory control levels (Saletti et al., 2022).

The three interacting space and time control layers (Saletti et al., 2022) are defined as follows:

- Distribution modules. Each of these modules manages energy distribution to a section of the heating and cooling network (Saletti et al. 2020) and provides the forecast of the heating and cooling requirements over a short-term prediction horizon (e.g. the following two days).

- **Short-Term Supervisory module**, namely **ShoTS**. It is a low-level supervisory controller which controls the thermal power station in real time, based on a short-term objective and prediction horizon. This layer receives (i) the demand forecast from the distribution modules, (ii) long-term constraints calculated by a high-level supervisory controller, and (iii) feedback on the actual operation of the system.
- **Long-Term Supervisory module**, namely **LoTS**. It is a high-level supervisory controller that (i) receives the actual system operation in the form of the cumulated energy and fuel consumed, (ii) solves the yearly scheduling problem of the thermal power station with a daily time resolution, thus including long-term factors, and (iii) generates the long-term constraints for ShoTS.

In the long run, real-time automatic control carried out by ShoTS should lead to the fulfillment of the yearly goals, since it is forced to follow indications given by LoTS.
These modules are Model Predictive Control agents and, hence, their calculations are repeated every time-step in order to provide an updated solution every time new information is available. The features of the modules regarding time parameters (i.e. prediction horizon and time resolution), objective function, constraints, available disturbances and problem type are summarized in Table 1.

Table 1. Features of the three main control modules of the Model Predictive Control strategy for small DHC developed in the project (Saletti et al., 2022).

	Distribution module	ShoTS module	LoTS module
Objective function	Minimize energy supplied to end-user	Minimize operating cost	Minimize yearly cost
Constraints	End-user indoor comfort temperature	Meet energy demand, plant operation, long-term constraints	Meet daily demand, efficiency incentives, contracts and maintenance
Disturbances	Outdoor temperature, occupation schedule	Energy demand, hourly cost of electricity	Energy demand, daily cost of electricity
Prediction horizon	2 days	2 days	Whole year
Time-step	15 minutes	15 minutes	1 day
Algorithm	Dynamic Programming	Mixed Integer Linear Programming	Linear Programming

2.2. Long-term supervisory module

The LoTS module solves an energy scheduling problem with reference to the energy produced daily by the energy conversion units in the thermal power station in order to match the daily energy demand of all energy vectors. Its objective is to define the daily energy production over the entire year to minimize the total operating cost (including the revenues from incentives such as the Energy Efficiency Titles for high efficiency cogeneration). The problem is a Linear Programming (LP) due to the sole presence of continuous variables.
With N being the number of days of the prediction horizon, the disturbances, optimization variables, required data, objective function and constraints are reported below.
Even though a seasonal storage is not present in the case study, the algorithm has been built by including the possibility to store and retrieve thermal energy from a seasonal storage tank.

This is characterized by the amount of energy that can be stored (State of Charge), charge and discharge efficiencies and percentage loss parameter.

NOTE: All units reported in the tables in the remainder of the deliverable are those used for the exchange of information and algorithms implementation in simulation environment and real case study. The implementation of the equations in this deliverable must be carried out with the consistency of the units.

Plant models

The plants in the thermal power station are modeled with a relationship between daily input energy and daily output energy characterized by a fixed nominal efficiency. This is exemplified in Eq. (1), written for plant j and day k:

$$E_{\mathrm{out,j,k}} = \eta_{\mathrm{j}} \; E_{\mathrm{in,j,k}} \tag{1}$$

The CHP efficiency is additionally corrected with the outdoor temperature T_{out} as follows:

$$\eta_{\mathrm{el,CHP,k}} = \gamma_{1,\mathrm{el}} \, T_{\mathrm{out,k}} + \gamma_{2,\mathrm{el}} \tag{2a}$$

$$\eta_{I,\mathrm{CHP,k}} = \begin{cases} \gamma_{1,\mathrm{I1}} \, T_{\mathrm{out,k}} + \gamma_{2,\mathrm{I1}} & \text{if } T_{\mathrm{out,k}} \leq T_{\mathrm{out,nom}} \\ \gamma_{1,\mathrm{I2}} \, T_{\mathrm{out,k}} + \gamma_{2,\mathrm{I2}} & \text{if } T_{\mathrm{out,k}} > T_{\mathrm{out,nom}} \end{cases} \tag{2b}$$

$$\eta_{\mathrm{th,CHP,k}} = \eta_{I,\mathrm{CHP,k}} - \eta_{\mathrm{el,CHP,k}} \tag{2c}$$

where η_{el}, η_{I} and η_{th} are the electrical, first principle and thermal efficiencies, and the coefficients γ are identified based on the data provided in the manufacturer's datasheets.

Disturbances

Description	Disturbance	Unit	Type	From
Daily heat demand	$E_{\mathrm{dem,h}}$	MWh	array	Prediction/historical
Daily cold demand	$E_{\mathrm{dem,c}}$	MWh	array	Prediction/historical
Daily electricity demand	$E_{\mathrm{dem,el}}$	MWh	array	Prediction/historical
Daily steam demand	$E_{\mathrm{dem,st}}$	MWh	array	Prediction/historical
Daily average outdoor temperature	T_{out}	°C	array	Prediction/historical
Daily cost of electricity sold to the grid	c_{s}	EUR/MWh	array	Prediction
Daily cost of electricity bought from the grid	c_{b}	EUR/MWh	array	Prediction

Optimization variables

Description	Variable	Unit	Type
B inlet energy	E_{B}	MWh	Continuous
CHP inlet energy	E_{CHP}	MWh	Continuous
CHP dissipated heat	E_{diss}	MWh	Continuous
ABS inlet heat	E_{ABS}	MWh	Continuous
SG fuel mass flow rate	E_{SG}	MWh	Continuous
EC inlet electricity	E_{EC}	MWh	Continuous

Grid bought electricity	E_{gb}	MWh	Continuous
Grid sold electricity	E_{gs}	MWh	Continuous
B maximum inlet energy	M_{B}	MWh	Continuous
CHP maximum inlet energy	M_{CHP}	MWh	Continuous
SG maximum inlet energy	M_{SG}	MWh	Continuous
Grid maximum bought electricity	M_{gb}	MWh	Continuous
Grid maximum sold electricity	M_{gs}	MWh	Continuous
B minimum inlet energy	m_{B}	MWh	Continuous
CHP minimum inlet energy	m_{CHP}	MWh	Continuous
SG minimum inlet energy	m_{SG}	MWh	Continuous
Grid minimum bought electricity	m_{gb}	MWh	Continuous
Grid minimum sold electricity	m_{gs}	MWh	Continuous
CHP useful electricity	$E_{\mathrm{el,CHP}}$	MWh	Continuous
CHP maximum useful electricity	$M_{\mathrm{el,CHP}}$	MWh	Continuous
CHP minimum useful electricity	$m_{\mathrm{el,CHP}}$	MWh	Continuous
CHP useful heat	$E_{\mathrm{th,CHP}}$	MWh	Continuous
CHP maximum useful heat	$M_{\mathrm{th,CHP}}$	MWh	Continuous
CHP minimum useful heat	$m_{\mathrm{th,CHP}}$	MWh	Continuous
St State of Charge (stored energy)	SoC_{St}	MWh	Continuous
St inlet heat	$E_{\mathrm{St,in}}$	MWh	Continuous
St outlet heat	$E_{\mathrm{St,out}}$	MWh	Continuous
B daily availability	ε_{B}	-	Continuous
CHP daily availability	$\varepsilon_{\mathrm{CHP}}$	-	Continuous
ABS daily availability	$\varepsilon_{\mathrm{ABS}}$	-	Continuous
SG daily availability	$\varepsilon_{\mathrm{SG}}$	-	Continuous
EC daily availability	$\varepsilon_{\mathrm{EC}}$	-	Continuous

Notes:

- The maximum (*M*) and minimum (*m*) variables constitute the boundaries of the corresponding energy variables. They are passed to the ShoTS module as long-term constraints.
- The daily availability (*ε*) is a continuous variable between 0 and 1. It reduces the maximum operation of plant j during day k. The variable is 0 if the plant is under maintenance or cannot operate during the given day.
- Finally, it is possible to vary the composition of the thermal station by varying the indexes of the variables corresponding to the different plant types.

Required data

Description	**Parameter**	**Unit**	**Type**	**Time variation**
Fuel lower heating value	LHV	MWh/kg	Scalar	Fixed
Cost of fuel	c_{f}	EUR/kg	Scalar	Fixed
Yearly parameters				
Maximum fuel consumption over the year	$M_{\mathrm{fuel,max,y}}$	kg	Scalar	Fixed
Minimum fuel consumption over the year	$M_{\mathrm{fuel,min,y}}$	kg	Scalar	Fixed
Maximum electricity sold to the grid over the year	$E_{\mathrm{gs,max,y}}$	MWh	Scalar	Fixed

Minimum electricity sold to the grid over the year	$E_{\mathrm{gs,min,y}}$	MWh	Scalar	Fixed
Maximum electricity bought from the grid over the year	$E_{\mathrm{gb,max,y}}$	MWh	Scalar	Fixed
Minimum electricity bought from the grid over the year	$E_{\mathrm{gb,min,y}}$	MWh	Scalar	Fixed
Minimum first principle efficiency for CHP	η_I	-	Scalar	Fixed
Minimum Primary Energy Saving	PES	-	Scalar	Fixed
Reference electrical/thermal efficiencies for PES	$\eta_{\mathrm{el}}/\eta_{\mathrm{th}}$	-	Scalar	Fixed
Factor for grid losses	p	-	Scalar	Fixed
Energy Efficiency Titles (EET) value	c_{EET}	EUR/MWh	Scalar	Fixed
Reference electrical/thermal efficiencies for EET calculation	$\eta_{\mathrm{el,EET}}/\eta_{\mathrm{th,EET}}$	-	Scalar	Fixed
Coefficient for EET calculation	K	-	Scalar	Fixed
Plant parameters				
Constant nominal efficiencies	η	-	array	Fixed
Upper operating boundaries	$\mathrm{in}_{\mathrm{max}}$	MWh	array	Fixed
Maximum yearly operating hours	OH	h	array]	Fixed
Maximum electricity sold to the grid daily	$E_{\mathrm{gs,max}}$	MWh	Scalar	Fixed
Maximum electricity bought from the grid daily	$E_{\mathrm{gb,max}}$	MWh	Scalar	Fixed
Seasonal storage parameters				
Maximum stored energy	$E_{\mathrm{St,max}}$	MWh	Scalar	Fixed
Maximum State of Charge	SoC_{max}	MWh	Scalar	Fixed
Minimum State of Charge	SoC_{min}	MWh	Scalar	Fixed
Initial State of Charge	SoC_0	MWh	Scalar	Updated at each new problem
Charge/discharge efficiencies	$\eta_{\mathrm{St,ch}}/\eta_{\mathrm{St,disch}}$	-	Scalar	Fixed
Maximum energy stored/retrieved daily	$E_{\mathrm{St,in,max}}$ $/E_{\mathrm{St,out,max}}$	MWh	Scalar	Fixed
Loss parameter	$\varepsilon_{\mathrm{loss}}$	-	Scalar	Fixed
Winter/summer day number in which energy cannot be stored/retrieved from storage	$days_{\mathrm{St,w}}$ $/days_{\mathrm{St,s}}$	-	array	Fixed
Cumulated parameters in the past up to current day				
Electrical energy produced by CHP	$E_{\mathrm{el,CHP}}^{\mathrm{past}}$	MWh	Scalar	Updated at each new problem
Thermal energy produced by CHP	$E_{\mathrm{th,CHP}}^{\mathrm{past}}$	MWh	Scalar	Updated at each new problem
Fuel energy used by CHP	$E_{\mathrm{f,CHP}}^{\mathrm{past}}$	MWh	Scalar	Updated at each new problem

Total fuel energy	$E_{\text{fuel}}^{\text{past}}$	MWh	Scalar	Updated at each new problem
Electrical energy bought by grid	$E_{\text{gb}}^{\text{past}}$	MWh	Scalar	Updated at each new problem
Electrical energy sold to grid	$E_{\text{gs}}^{\text{past}}$	MWh	Scalar	Updated at each new problem

Constraints

The constraints, for better clarity, have been divided into different groups depending on their type and purpose. They are summarized in Table 2 and detailed in the following paragraphs.

Table 2. Summary of constraint types of the LoTS module.

Constraint number	Description
Lower and upper boundaries	Boundaries on the variables
I	Satisfy daily demand of all energy vectors at each day
II	Operational boundaries of all plants at each day
III	Maximum and minimum variables constraints
IV	Contractual/yearly constraints
V	Seasonal storage constraints
VI	Operating hours constraints

- Lower and upper boundaries:

All variables have to be positive, thus they are constrained between 0 and infinite. The State of Charge and energy variables of the seasonal storage (if present) are subject to the following upper (ub) and lower boundaries (lb) for each day k:

$$lb(SoC_{\text{St,k}}) = SoC_{\text{min}}$$
$$ub(SoC_{\text{St,k}}) = SoC_{\text{max}}$$
$$ub(E_{\text{St,in,k}}) = E_{\text{St,in,max}}$$
$$ub(E_{\text{St,out,k}}) = E_{\text{St,out,max}}$$

They are further updated according to winter (energy cannot be stored during defined winter days) and summer days (energy cannot be retrieved during summer), as follows:

$$ub(E_{\text{St,in,k}}) = 0 \quad \forall \; \mathbf{k} \in \boldsymbol{days}_{\mathbf{St,w}}$$
$$ub(E_{\text{St,out,k}}) = 0 \quad \forall \; \mathbf{k} \in \boldsymbol{days}_{\mathbf{St,s}}$$

The daily electricity exchange is bound as follows, for each day k:

$$ub(E_{\text{gb,k}}) = E_{\text{gb,max}}$$
$$ub(E_{\text{gs,k}}) = E_{\text{gs,max}}$$

Finally, the upper boundaries for the daily availability variables are set as 1:

$$ub(\varepsilon_{\text{j,k}}) = 1 \quad \forall \textbf{ day k, } \forall \textbf{ plant j}$$

- Constraints I

∀ day k:

$$\sum_{\text{j}} (\eta_{\text{B,j}} E_{\text{B,j,k}}) + E_{\text{th,CHP,k}} - E_{\text{ABS,k}} - E_{\text{St,in,k}} + E_{\text{St,out,k}} = E_{\text{dem,h,k}}$$

$$\sum_{j}(\eta_{EC,j}E_{EC,j,k}) + E_{ABS,k} = E_{dem,c,k}$$
$$E_{el,CHP,k} - \sum_{j} E_{EC,j,k} + E_{gb,k} - E_{gs,k} = E_{dem,el,k}$$
$$\sum_{j}(\eta_{SG,j}E_{SG,j,k}) = E_{dem,st,k}$$

- Constraints II

∀ day k:
$E_{el,CHP,k} - \eta_{el,CHP,k}\, E_{CHP,k} = 0$ (equality of useful electricity produced by CHP)
$E_{th,CHP,k} - \eta_{th,CHP,k}\, E_{CHP,k} + E_{diss,k} = 0$ (equality of useful heat produced by CHP)
$M_{el,CHP,k} - \eta_{el,CHP,k}\, M_{CHP,k} = 0$ (equality of maximum useful electricity produced by CHP)
$M_{th,CHP,k} - \eta_{th,CHP,k}\, M_{CHP,k} + E_{diss,k} = 0$ (equality of maximum useful heat produced by CHP)
$m_{el,CHP,k} - \eta_{el,CHP,k}\, m_{CHP,k} = 0$ (equality of maximum useful electricity produced by CHP)
$m_{th,CHP,k} - \eta_{th,CHP,k}\, m_{CHP,k} + E_{diss,k} = 0$ (equality of maximum useful heat produced by CHP)

∀ day k and ∀ plant j:
$\mathrm{in}_{j,k} \le \mathrm{in}_{max,j}$
∀ day k:
$-E_{th,CHP,k} + E_{ABS,k} \le 0$ (inequality of heat from the CHP)

- Constraints III

∀ day k and ∀ j variable that has a maximum variable M and a minimum variable m:
$E_{j,k} - \mathrm{M}_{j,k} \le 0$
$-E_{j,k} + m_{j,k} \le 0$
∀ day k and ∀ j of plants working with fuel (B, CHP, SG):
$\mathrm{M}_{f,j,k} \le \mathrm{in}_{max,f,j}$

where:

- $E = [E_B, E_{CHP}, E_{SG}, E_{gb}, E_{gs}, E_{el,CHP}, E_{th,CHP}]$
- $M = [M_B, M_{CHP}, M_{SG}, M_{gb}, M_{gs}, M_{el,CHP}, M_{th,CHP}]$ (maxima of variables **E**)
- $m = [m_B, m_{CHP}, m_{SG}, m_{gb}, m_{gs}, m_{el,CHP}, m_{th,CHP}]$ (minima of variables **E**)
- $M_f = [M_B, M_{CHP}, M_{SG}]$ (maxima of plants working with fuel)

- Constraints IV

$\sum_k(\sum_j M_{B,j,k} + M_{CHP,k} + \sum_j M_{SG,j,k}) \le M_{fuel,max,y}\, LHV - E_{fuel}^{past}$ (max yearly fuel consumption)
$\sum_k(-\sum_j m_{B,j,k} - m_{CHP,k} - \sum_j m_{SG,j,k}) \le -M_{fuel,min,y}\, LHV + E_{fuel}^{past}$ (min yearly fuel consumption)
$\sum_k M_{gb,k} \le E_{gb,max,y} - E_{gb}^{past}$ (max yearly bought electricity)
$-\sum_k m_{gb,k} \le -E_{gb,min,y} + E_{gb}^{past}$ (min yearly bought electricity)
$\sum_k M_{gs,k} \le E_{gs,max,y} - E_{gs}^{past}$ (max yearly sold electricity)
$-\sum_k m_{gs,k} \le -E_{gs,min,y} + E_{gs}^{past}$ (min yearly sold electricity)
$\sum_k(\eta_I\, m_{CHP,k} - m_{el,CHP} - m_{th,CHP}) \le E_{el,CHP}^{past} + E_{th,CHP}^{past} - \eta_I\, E_{f,CHP}^{past}$ (first principle efficiency)

$$\sum_k \left(m_{CHP,k} - \frac{1-PES}{\eta_{el}\, p} m_{el,CHP} - \frac{1-PES}{\eta_{th}} m_{th,CHP} \right) \leq \left(\frac{E_{el,CHP}^{past}}{\eta_{el}\, p} + \frac{E_{th,CHP}^{past}}{\eta_{th}} \right) (1 - PES) - E_{f,CHP}^{past} \quad \text{(PES)}$$

∀ plant j:

$\sum_k \varepsilon_{j,k} \leq \frac{OH_j}{24}$ (max yearly operating hours for each plant)

- Constraints V

For the first time-step:

$SoC_{St,1} = SoC_0$

∀ k = 1 ... N-1:

$$SoC_{St,k+1} - (1 - \varepsilon_{loss})\, SoC_{St,k} - \eta_{St,ch} E_{St,in,k} + \frac{1}{\eta_{St,disch}} E_{St,out,k} = 0$$

- Constraints VI

∀ day k and ∀ plant j:

$\text{in}_{\varepsilon,j,k} - \text{in}_{max,j} \varepsilon_{j,k} \leq 0$

where: $\text{in}_\varepsilon = [M_B, M_{CHP}, E_{ABS}, M_{SG}, E_{EC}]$

Cost function

The cost function is the total cost of operation from the current day to the final day of the year. It includes the contributions of the fuel purchased, the electrical energy purchased from the power grid, the revenues from the electrical energy injected into the power grid as well as the revenues from the white certificates, that are awarded at the end of the year to the CHP plants that meet the high efficiency cogeneration criteria (a minimum first principle efficiency and a minimum Primary Energy Saving):

$$\sum_k \left[\frac{c_f}{LHV} \left(\sum_j E_{B,j,k} + \sum_j E_{SG,j,k} \right) + \left(\frac{c_f}{LHV} + c_{EET} \right) E_{CHP,k} + c_{b,k} E_{gb,k} - c_{s,k} E_{gs,k} - \frac{c_{EET}}{\eta_{el,EET}\, p} E_{el,CHP,k} - \frac{c_{EET}}{\eta_{th,EET}} E_{th,CHP,k} \right]$$

2.3. Short-term supervisory module

The ShoTS module solves a highly detailed unit commitment problem which is further bound with the long-term constraints calculated and sent by the LoTS module. Its objective is to define the operation of the energy conversion units in the thermal power station in order to minimize the operating cost over a short-term prediction horizon. The problem is a Mixed Integer Linear Programming (MILP) due to the presence of continuous and binary variables.
With *N* being the number of time-steps of the prediction horizon, the disturbances, optimization variables, required data, objective function and constraints are reported below. In addition, the model of all plants in the thermal power station is described.

Plant models

The plants in the thermal power station are modeled with linear performance curves between the plant input **in** (fuel power for B, CHP, SG, thermal power for ABS, electrical power for EC) and the plant output **out** (thermal power for B and SG, electrical and thermal power for CHP, cold power for ABS and EC), as in Eq. (3), written for plant j and time-step k:

$$\mathrm{out}_{\mathrm{j,k}} = \alpha_{\mathrm{j}} \cdot \mathrm{in}_{\mathrm{j,k}} + \beta_{\mathrm{j}} \cdot \delta_{\mathrm{j,k}} \tag{3}$$

The performance coefficient of the curve, which can be determined based on the operating points reported in the manufacturers' datasheets, are given in Eqs. (4):

$$\alpha_{\mathrm{j}} = \frac{\mathrm{out}_{\mathrm{j,max}} - \mathrm{out}_{\mathrm{j,min}}}{\mathrm{in}_{\mathrm{j,max}} - \mathrm{in}_{\mathrm{j,min}}} \tag{4a}$$

$$\beta_{\mathrm{j}} = \mathrm{out}_{\mathrm{j,max}} - \alpha_{\mathrm{j}} \cdot \mathrm{in}_{\mathrm{j,max}} \tag{4b}$$

This approach can be easily extended (with the addition of proper auxiliary binary and continuous variables) to piecewise linear performance curves.
Moreover, the plants are divided into the following two groups:

- **Type A** (B, CHP, SG): plants that can be in idle mode or standby mode, i.e. the plant is kept warm but is not producing.
- **Type B** (ABS, EC): plants that cannot be in idle mode or standby mode.

Disturbances

Description	Disturbance	Unit	Type	From
Total heat demand	$\dot{Q}_{\mathrm{dem,h}}$	kW	array	Distribution modules
Total cold demand	$\dot{Q}_{\mathrm{dem,c}}$	kW	array	Distribution modules
Total electricity demand	$P_{\mathrm{dem,el}}$	kW	array	Other prediction module
Total steam demand	$\dot{Q}_{\mathrm{dem,st}}$	kW	array	Other prediction module
Cost of electricity sold to the grid	c_{s}	EUR/kWh	array	Other prediction module
Cost of electricity bought from the grid	c_{b}	EUR/kWh	array	Other prediction module

Optimization variables

Description	Variable	Unit	Type
B fuel mass flow rate	$\dot{m}_{\mathrm{B}}$	kg/s	Continuous
CHP fuel mass flow rate	$\dot{m}_{\mathrm{CHP}}$	kg/s	Continuous
CHP dissipated heat	$\dot{Q}_{\mathrm{diss}}$	kW	Continuous
ABS inlet heat	$\dot{Q}_{\mathrm{ABS}}$	kW	Continuous
SG fuel mass flow rate	$\dot{m}_{\mathrm{SG}}$	kg/s	Continuous
EC inlet electricity	P_{EC}	kW	Continuous
Grid bought electricity	P_{gb}	kW	Continuous
B switch	δ_{B}	-	Binary
CHP switch	δ_{CHP}	-	Binary
ABS switch	δ_{ABS}	-	Binary
SG switch	δ_{SG}	-	Binary

EC switch	δ_{EC}	-	Binary
Grid sold electricity	P_{gs}	kW	Continuous
B start-up cost	SU_{B}	kg	Continuous
CHP start-up cost	SU_{CHP}	kg	Continuous
ABS start-up cost	SU_{ABS}	kJ	Continuous
SG start-up cost	SU_{SG}	kg	Continuous
EC start-up cost	SU_{EC}	kJ	Continuous
B idle switch	γ_{B}	-	Binary
CHP idle switch	γ_{CHP}	-	Binary
SG idle switch	γ_{SG}	-	Binary

Notes:

- The start-up cost of plant j is the additional inlet energy that must be fed in case of a start-up (fuel mass for B, CHP and SG, thermal energy for ABS, electrical energy for EC)
- The switch (δ) of plant j is 0 if the plant is not producing and 1 if the plant is producing.
- The idle switch (γ) of plant j is 0 if the plant is not in idle or stand-by mode (δ can be 0 or 1) and 1 if the plant is in idle mode (δ must be 0, since there is no production). This variable is present only for plants A.
- Finally, it is possible to vary the composition of the thermal power station by varying the indexes of the variables corresponding to the different plant types.

Required data

Description	Parameter	Unit	Type	Time variation
Fuel lower heating value	LHV	kJ/kg	Scalar	Fixed
Maximum electrical power sold to the grid	$P_{\mathrm{gs,max}}$	kW	Scalar	Fixed
Maximum electrical power bought from the grid	$P_{\mathrm{gb,max}}$	kW	Scalar	Fixed
Performance curve first coefficient	α	-	array	Fixed
Performance curve second coefficient	β	kW	array	Fixed
Upper operating boundaries	$\mathrm{in}_{\mathrm{max}}$	kg/s (B, CHP, SG) or kW (ABS, EC)	array	Fixed
Lower operating boundaries	$\mathrm{in}_{\mathrm{min}}$	kg/s (B, CHP, SG) or kW (ABS, EC)	array	Fixed
Upper ramp boundaries	$\mathrm{ramp\_up}$	kg/s (B, CHP, SG) or kW (ABS, EC)	array	Fixed
Lower ramp boundaries	$\mathrm{ramp\_down}$	kg/s (B, CHP, SG) or kW (ABS, EC)	array	Fixed
Start-up costs (additional fuel mass or energy during start-up)	C_{SU}	kg (B, CHP, SG) or kJ (ABS, EC)	array	Fixed
Idle costs (additional fuel mass in idle mode)	C_{γ}	kg (B, CHP, SG)	array	Fixed
Minimum up-time	UT	-	array	Fixed

Minimum down-time	DT	-	array	Fixed
Number of up-time steps prior to prediction horizon	UT_0	-	array	Updated at each new problem
Number of down-time steps prior to prediction horizon	DT_0	-	array	Updated at each new problem
Initial states	δ_0	-	array	Updated at each new problem
Initial idle states	γ_0	-	array	Updated at each new problem

Constraints

The constraints, for better clarity, have been divided into different groups depending on their type and purpose. They are summarized in Table 3 and detailed in the following paragraphs.

Table 3. Summary of constraint types of the ShoTS module.

Constraint number	Description
Lower and upper boundaries	Boundaries on the variables
I	Satisfy demand of all energy vectors at all time-steps
II	Operational boundaries of all plants at each time-step
III	Ramp constraints
IV	Long-term constraints (from LoTS module)
V	Start-up costs
VI	Hierarchical constraints (to avoid problem symmetry)
VII	Minimum up-time and down-time
VIII	Maximum number of start-ups in the prediction horizon

- Lower and upper boundaries:

All variables have to be positive, thus they are constrained between 0 and infinite. Binary variables are constrained between 0 and 1, or obvious reasons. As for the grid exchange variables, they are subject to the following upper constraints:

$P_{\mathrm{gb,k}} \le P_{\mathrm{gb,max}}$ and $P_{\mathrm{gs,k}} \le P_{\mathrm{gs,max}}$ **∀ time-step k**

If a plant is under maintenance for a given time interval, the upper boundary of the switch (variable δ) at the corresponding time-steps is updated as 0.

- Constraints I

∀ time-step k:

$$\sum_{\mathrm{j}} (\alpha_{\mathrm{B,j}} LHV \dot{m}_{\mathrm{B,j,k}} + \beta_{\mathrm{B,j}} \delta_{\mathrm{B,j,k}}) + (\alpha_{\mathrm{CHP,h}} LHV \dot{m}_{\mathrm{CHP,k}} + \beta_{\mathrm{CHP,h}} \delta_{\mathrm{CHP,k}}) - \dot{Q}_{\mathrm{ABS,k}} - \dot{Q}_{\mathrm{diss,k}} - \frac{SU_{\mathrm{ABS,k}}}{\Delta t} = \dot{Q}_{\mathrm{dem,h,k}}$$

$$\sum_{\mathrm{j}} (\alpha_{\mathrm{EC,j}} P_{\mathrm{EC,j,k}} + \beta_{\mathrm{EC,j}} \delta_{\mathrm{EC,j,k}}) + (\alpha_{\mathrm{ABS}} \dot{Q}_{\mathrm{ABS,k}} + \beta_{\mathrm{ABS}} \delta_{\mathrm{ABS,k}}) = \dot{Q}_{\mathrm{dem,c,k}}$$

$$\left(\alpha_{\mathrm{CHP,el}} LHV \dot{m}_{\mathrm{CHP,k}} + \beta_{\mathrm{CHP,el}} \delta_{\mathrm{CHP,k}}\right) - \sum_{\mathrm{j}} \left(P_{\mathrm{EC,j,k}} + \frac{SU_{\mathrm{EC,j,k}}}{\Delta t}\right) + P_{\mathrm{gb,k}} - P_{\mathrm{gs,k}} = P_{\mathrm{dem,el,k}}$$
$$\sum_{\mathrm{j}} (\alpha_{\mathrm{SG,j}} LHV \dot{m}_{\mathrm{SG,j,k}} + \beta_{\mathrm{SG,j}} \delta_{\mathrm{SG,j,k}}) = \dot{Q}_{\mathrm{dem,st,k}}$$

- <u>Constraints II</u>

∀ time-step k and ∀ plant j:

$$\mathrm{in}_{\mathrm{j,k}} - \mathrm{in}_{\mathrm{j,max}} \delta_{\mathrm{j,k}} \leq 0$$
$$-\mathrm{in}_{\mathrm{j,k}} + \mathrm{in}_{\mathrm{j,min}} \delta_{\mathrm{j,k}} \leq 0$$

∀ time-step k:

$-\left(\alpha_{\mathrm{CHP,h}} LHV \dot{m}_{\mathrm{CHP,k}} + \beta_{\mathrm{CHP,h}} \delta_{\mathrm{CHP,k}}\right) + \dot{Q}_{\mathrm{ABS,k}} + \dot{Q}_{\mathrm{diss,k}} \leq 0$ (inequality of heat from the CHP)

- <u>Constraints III</u>

∀ k = 1 ... N-1 and ∀ plant j:

$$\mathrm{in}_{\mathrm{j,k+1}} - \mathrm{in}_{\mathrm{j,k}} \leq \mathrm{ramp\_up}_{\mathrm{j}}$$
$$-\mathrm{in}_{\mathrm{j,k+1}} + \mathrm{in}_{\mathrm{j,k}} \leq -\mathrm{ramp\_down}_{\mathrm{j}}$$

- <u>Constraints IV</u>

$\sum_{\mathrm{k}} \left(\alpha_{\mathrm{CHP,el}} LHV \dot{m}_{\mathrm{CHP,k}} + \beta_{\mathrm{CHP,el}} \delta_{\mathrm{CHP,k}}\right) \Delta t \leq E_{\mathrm{CHP,max}}$ (maximum CHP production)

$\sum_{\mathrm{k}} \left(-\alpha_{\mathrm{CHP,el}} LHV \dot{m}_{\mathrm{CHP,k}} - \beta_{\mathrm{CHP,el}} \delta_{\mathrm{CHP,k}}\right) \Delta t \leq -E_{\mathrm{CHP,min}}$ (minimum CHP production)

$\sum_{\mathrm{k}} \left(\sum_{\mathrm{j}} \dot{m}_{\mathrm{B,j,k}} + \dot{m}_{\mathrm{CHP,k}} + \sum_{\mathrm{j}} \dot{m}_{\mathrm{SG,j,k}}\right) \Delta t \leq M_{\mathrm{max}}$ (maximum fuel production)

$\sum_{\mathrm{k}} \left(-\sum_{\mathrm{j}} \dot{m}_{\mathrm{B,j,k}} - \dot{m}_{\mathrm{CHP,k}} - \sum_{\mathrm{j}} \dot{m}_{\mathrm{SG,j,k}}\right) \Delta t \leq -M_{\mathrm{min}}$ (minimum fuel production)

$\sum_{\mathrm{k}} P_{\mathrm{gb,k}} \Delta t \leq E_{\mathrm{gb,max}}$ (maximum bought electricity over prediction horizon)

$-\sum_{\mathrm{k}} P_{\mathrm{gb,k}} \Delta t \leq -E_{\mathrm{gb,min}}$ (minimum bought electricity over prediction horizon)

$\sum_{\mathrm{k}} P_{\mathrm{gs,k}} \Delta t \leq E_{\mathrm{gs,max}}$ (maximum sold electricity over prediction horizon)

$-\sum_{\mathrm{k}} P_{\mathrm{gs,k}} \Delta t \leq -E_{\mathrm{gs,min}}$ (minimum sold electricity over prediction horizon)

$\sum_{\mathrm{k}} \delta_{\mathrm{CHP,k}} \Delta t \leq T_{\mathrm{CHP,max}}$ (maximum operating hours of the CHP)

$-\sum_{\mathrm{k}} \delta_{\mathrm{CHP,k}} \Delta t \leq -T_{\mathrm{CHP,min}}$ (minimum operating hours of the CHP)

- <u>Constraints V</u>

For the first time-step k = 1 and ∀ j of plants A:

$$C_{\mathrm{SU,j}} \delta_{\mathrm{j,1}} - SU_{\mathrm{j,1}} \leq C_{\mathrm{SU,j}} \left(\delta_{\mathrm{j,0}} + \gamma_{\mathrm{j,0}}\right)$$
$$\gamma_{\mathrm{j,1}} \leq \delta_{\mathrm{j,0}} + \gamma_{\mathrm{j,0}}$$

∀ k = 1 ... N-1 and ∀ j of plants A:

$$C_{\mathrm{SU,j}} \delta_{\mathrm{j,k+1}} - C_{\mathrm{SU,j}} \delta_{\mathrm{j,k}} - C_{\mathrm{SU,j}} \gamma_{\mathrm{j,k}} - SU_{\mathrm{j,k+1}} \leq 0$$
$$\delta_{\mathrm{j,k}} + \gamma_{\mathrm{j,k}} \leq 1$$
$$\gamma_{\mathrm{j,k+1}} - \gamma_{\mathrm{j,k}} - \delta_{\mathrm{j,k}} \leq 0$$

For the first time-step k = 1 and ∀ j of plants B:

$$C_{\mathrm{SU,j}} \delta_{\mathrm{j,1}} - SU_{\mathrm{j,1}} \leq C_{\mathrm{SU,j}} \delta_{\mathrm{j,0}}$$

∀ k = 1 ... N-1 and ∀ j of plants B:
$C_{SU,j}\delta_{j,k+1} - C_{SU,j}\delta_{j,k} - SU_{j,k+1} \leq 0$

Notes:

- The start-up is positive only when there is effectively a start-up. When the plant is left in idle mode, there is no start-up. Moreover, the plant cannot be in idle mode if it was completely off at the previous time-step. The possible variable combinations are represented in the following following table.

γ_k	δ_k	γ_{k+1}
0	0	0
1	0	0 ∪ 1
0	1	0 ∪ 1

- The initial conditions $\delta_{j,0}$ and $\gamma_{j,0}$ represent the actual plant state at the beginning of the prediction horizon.

- Constraints VI

∀ time-step k and ∀ j of B, SG and EC:
$-\delta_{B,j,k} + \delta_{B,j+1,k} \leq 0$
$-\delta_{SG,j,k} + \delta_{SG,j+1,k} \leq 0$
$-\delta_{EC,j,k} + \delta_{EC,j+1,k} \leq 0$

- Constraints VII

∀ j of plants A with *UT*$_j$ > 1:
First time-step:
1) If $UT_{n,j} > 0$: $\sum_{k=1}^{UT_{n,j}}(-\delta_{j,k} - \gamma_{j,k}) \leq -UT_{n,j}$
2) If $UT_{n,j} = 0$: $(UT_j - 1)(\delta_{j,1} + \gamma_{j,1}) - \sum_{k=2}^{UT_{n,j}}(\delta_{j,k} + \gamma_{j,k}) \leq UT_j(\delta_{j,0} + \gamma_{j,0})$
∀ k = *UT*$_{n,j}$ + 1 … N - *UT*$_j$ + 1:

$$-UT_j(\delta_{j,k-1} + \gamma_{j,k-1}) + (UT_j - 1)(\delta_{j,k} + \gamma_{j,k}) - \sum_{n=k+1}^{k+UT_j-1}(\delta_{j,n} + \gamma_{j,n}) \leq 0$$

∀ k = N - *UT*$_j$ + 2 … N:

$$-(N - k + 1)(\delta_{j,k-1} + \gamma_{j,k-1}) + (N - k)(\delta_{j,k} + \gamma_{j,k}) - \sum_{n=k+1}^{N}(\delta_{j,n} + \gamma_{j,n}) \leq 0$$

∀ j of plants A with *DT*$_j$ > 1:
First time-step:
1) If $DT_{n,j} > 0$: $\sum_{k=1}^{DT_{n,j}}(\delta_{j,k} + \gamma_{j,k}) \leq 0$
2) If $DT_{n,j} = 0$: $(1 - DT_j)(\delta_{j,1} + \gamma_{j,1}) + \sum_{k=2}^{DT_{n,j}}(\delta_{j,k} + \gamma_{j,k}) \leq DT_j\,(1 - \delta_{j,0} - \gamma_{j,0})$
∀ k = *DT*$_{n,j}$ + 1 … N - *DT*$_j$ + 1:

$$DT_j(\delta_{j,k-1} + \gamma_{j,k-1}) + (1 - DT_j)(\delta_{j,k} + \gamma_{j,k}) + \sum_{n=k+1}^{k+DT_j-1}(\delta_{j,n} + \gamma_{j,n}) \leq DT_j$$

∀ k = N - *DT*$_j$ + 2 … N:

$$(N-k+1)(\delta_{j,k-1}+\gamma_{j,k-1})-(N-k)(\delta_{j,k}+\gamma_{j,k})+\sum_{n=k+1}^{N}(\delta_{j,n}+\gamma_{j,n})\leq N-k+1$$

∀ j of plants B with UT_j > 1:
First time-step:

1) If $UT_{n,j}>0$: $\sum_{k=1}^{UT_{n,j}}-\delta_{j,k}\leq -UT_{n,j}$
2) If $UT_{n,j}=0$: $(UT_j-1)\delta_{j,1}-\sum_{k=2}^{UT_{n,j}}\delta_{j,k}\leq UT_j\delta_{j,0}$

∀ k = $UT_{n,j}$ + 1 … N - UT_j + 1:

$$-UT_j\delta_{j,k-1}+(UT_j-1)\delta_{j,k}-\sum_{n=k+1}^{k+UT_j-1}\delta_{j,n}\leq 0$$

∀ k = N - UT_j + 2 … N:

$$-(N-k+1)\delta_{j,k-1}+(N-k)\delta_{j,k}-\sum_{n=k+1}^{N}\delta_{j,n}\leq 0$$

∀ j plant with DT_j > 1 (minimum down-time is more than one time-step):
First time-step:

1) If $DT_{n,j}>0$: $\sum_{k=1}^{DT_{n,j}}\delta_{j,k}\leq 0$
2) If $DT_{n,j}=0$: $(1-DT_j)\delta_{j,1}+\sum_{k=2}^{DT_{n,j}}\delta_{j,k}\leq DT_j\,(1-\delta_{j,0})$

∀ k = $DT_{n,j}$ + 1 … N - DT_j + 1:

$$DT_j\delta_{j,k-1}+(1-DT_j)\delta_{j,k}+\sum_{n=k+1}^{k+DT_j-1}\delta_{j,n}\leq DT_j$$

∀ k = N - DT_j + 2 … N:

$$(N-k+1)\delta_{j,k-1}-(N-k)\delta_{j,k}+\sum_{n=k+1}^{N}\delta_{j,n}\leq N-k+1$$

- Constraints VIII

∀ plant j:

$$\sum_{k}SU_{j,k}\leq N_{SU,j,max}\cdot C_{SU,j}$$

Cost function

The cost function is the total operating cost of the short-term prediction horizon and includes the contributions of the fuel used to operate the plants (including the additional fuel for start-ups and for keeping the plants in stand-by), the electricity purchased from the power grid and the revenues from the electricity injected into the power grid:

$$\sum_{k}\Bigg[c_f\left(\sum_{j}\dot{m}_{B,j,k}+\dot{m}_{CHP,k}+\sum_{j}\dot{m}_{SG,j,k}\right)\Delta t+c_f\left(\sum_{j}SU_{B,j,k}+SU_{CHP,k}+\sum_{j}SU_{SG,j,k}\right) + c_f\left(\sum_{j}C_{\gamma,j}\gamma_{B,j,k}+C_{\gamma,CHP}\gamma_{CHP,k}+\sum_{j}C_{\gamma,j}\gamma_{SG,j,k}\right)+c_{b,k}P_{gb,k}\Delta t-c_{s,k}P_{gs,k}\Delta t\Bigg]$$

2.4. Communication between modules

A fundamental part of the algorithm is the communication between the ShoTS and LoTS modules. Indeed, the LoTS constraints the ShoTS, leading it to operate in such a way that the yearly goals are more likely to be met at the end of the year.

From Section 2.2, it can be noted that the LoTS problem contains auxiliary maximum and minimum variables (*M* and *m*, respectively). These variables bind the actual energy variables E and determine an optimal band for their operation, illustrated in a qualitative way in Figure 3. The first part of these optimal bands (indicated by the values of *M* and *m* corresponding to the number of days of the ShoTS prediction horizon), is used as a long-term constraint to further bind the ShoTS problem and push it toward a solution that also meets the LoTS yearly goals, as mentioned.

These optimal bands of operation are updated continuously during real-time operation, i.e. daily, every LoTS calculation. The timeline of the LoTS problem is schematized in Figure 4. At the current day, the LoTS problem defined in Section 2.2 is written for the future period of the year (blue bar). The measurements from the real system (or from its digital twin built in D2.2) are exploited to calculate the actual operation and consumption, and to update the cumulated parameters (e.g. energy, fuel, and operating hours) of the previous period of the year (red bar). These cumulated parameters are defined "Cumulated parameters in the past up to current day" in the table of the required data of the LoTS problem. Once the LoTS solution has been found, the horizon is diminished by one day and a new problem is solved.

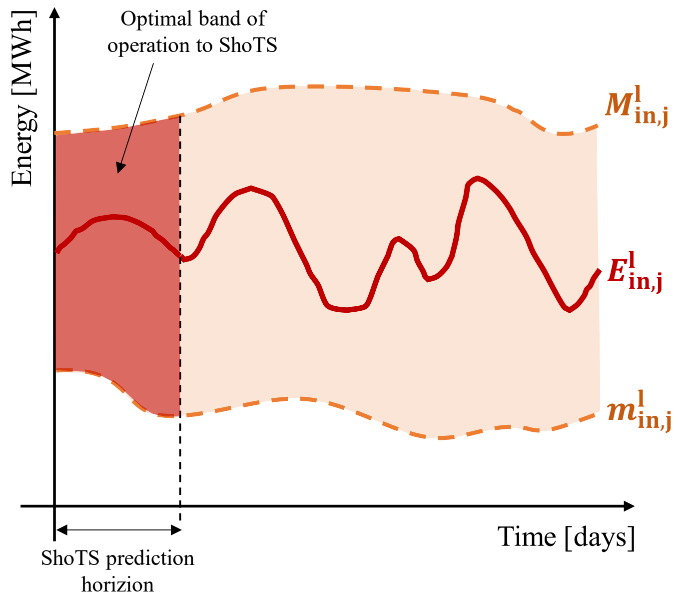

Figure 3. Qualitative representation of the optimal band of operation as long-term constraints determined by the maximum and minimum auxiliary variables in the LoTS problem. (Saletti et al., 2022).

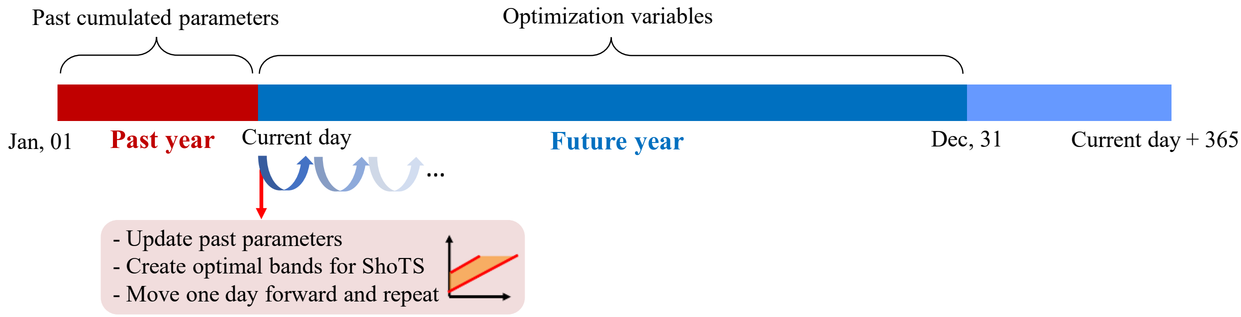

Figure 4. Timeline and update of the LoTS problem. (Saletti et al., 2022).

Every day, whenever a new LoTS calculation has been completed, the parameters of the long-term constraints of the ShoTS problem (Constraints IV in Table 3. Summary of constraint types of the ShoTS module.Table 3) are updated as follows.
Given ***L*** **the solution of the last LoTS** problem and N_d the number of days of the ShoTS prediction horizon:

- $E_{\mathrm{CHP,max}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.M}_{\mathbf{el,CHP,k}}$
- $E_{\mathrm{CHP,min}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.m}_{\mathbf{el,CHP,k}}$
- $M_{\mathrm{max}} = \sum_{k=1}^{N_\mathrm{d}} \left[\sum_j \boldsymbol{L.M}_{\mathbf{B,j,k}} + \boldsymbol{L.M}_{\mathbf{CHP,k}} + \sum_j \boldsymbol{L.M}_{\mathbf{SG,j,k}}\right] \cdot \frac{1}{LHV}$
- $M_{\mathrm{min}} = \sum_{k=1}^{N_\mathrm{d}} \left[\sum_j \boldsymbol{L.m}_{\mathbf{B,j,k}} + \boldsymbol{L.m}_{\mathbf{CHP,k}} + \sum_j \boldsymbol{L.m}_{\mathbf{SG,j,k}}\right] \cdot \frac{1}{LHV}$
- $E_{\mathrm{gb,max}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.M}_{\mathbf{gb,k}}$
- $E_{\mathrm{gb,min}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.m}_{\mathbf{gb,k}}$
- $E_{\mathrm{gs,max}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.M}_{\mathbf{gs,k}}$
- $E_{\mathrm{gs,min}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.m}_{\mathbf{gs,k}}$
- $T_{\mathrm{CHP,max}} = \sum_{k=1}^{N_\mathrm{d}} \boldsymbol{L.\varepsilon}_{\mathbf{CHP,k}}$

Moreover, the upper boundaries of the plant switches are updated if the LoTS determines that a plant must be off for a given period. This is implemented as follows, for each plant j and each day *d* = 1… N_d:

- If $\boldsymbol{L.\varepsilon}_{\mathbf{j,d}} = \mathbf{0}$
  - $ub\left(\delta_{\mathrm{j,k}}\right) = 0 \quad \forall\, \boldsymbol{k} \in [(\boldsymbol{d}-\mathbf{1}) * \mathbf{24} * \mathbf{4} + \mathbf{1},\ \boldsymbol{d} * \mathbf{24} * \mathbf{4}]$

3. Implementation and software specifications

The control architecture developed in Section 2 can be implemented in the real case study (or in simulation environment through the digital twin described in D2.2) according to the flowchart in Figure 5.

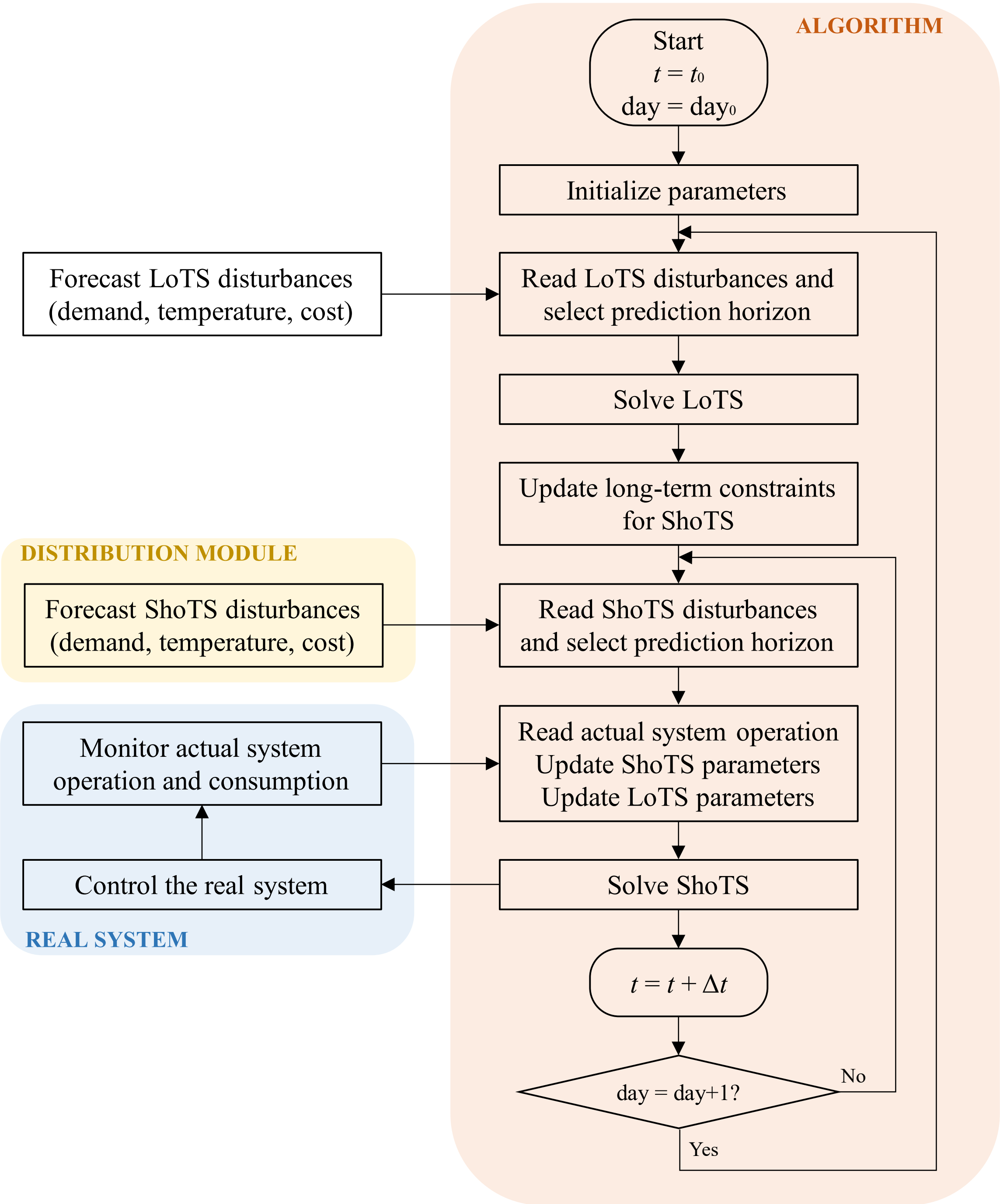

Figure 5. Block diagram of the implementation of the control architecture to the real system. (Saletti et al., 2022).

Before the simulation or the real system operation start, the parameters of the system are initialized. The disturbances of the LoTS module are forecast, and its parameters are selected. The LoTS problem described in Section 2.2, from the current day to the end of the year, is solved and the optimal solution is used to update the long-term constraints according to

Section 2.4. Then, the disturbances for the ShoTS are obtained from the distribution module of from another forecasting method. The data from system operation (i.e. real-time monitoring for the real system or simulation data for the digital twin) are collected and used to update the initial conditions and cumulated parameters of the ShoTS and LoTS problems respectively. The ShoTS problem (Section 2.3) updated in this way is solved, and the first time-step of the solution is used to determine the new set-points that are sent back for controlling the system. After a time-step has passed and the system has been controlled with the new time-steps, the part of procedure from the ShoTS disturbance update to the ShoTS solution is repeated, and this is carried out continuously. After a day of operation, the entire procedure, from the LoTS update to the end, is repeated. This goes automatically and ensures both real-time control and yearly scheduling.

The software implementation has been done in MATLAB® for the simulation and testing in the Model-in-the-Loop environment (Saletti et al., 2022).
As for the implementation in the real test site, which is the objective of WP3, in order to avoid license and compatibility issues, the ShoTS and LoTS modules and the communication protocols have been translated in Python.
The following software specifications are required for the implementation of the control protocol in the computer of the Cona Hospital:

- The entire procedure is carried on automatically by means of a scheduler.
- The ShoTS and LoTS parameters are declared in two separate .json files, which are called by the related modules. This gives the possibility to change relevant parameters manually during system operation (e.g. cost of fuel), if required.
- The ShoTS and LoTS disturbances are passed through two separate .csv files, together with the datetime. This is used to select the dataset with respect to the current datetime.
- The output of the control protocol is returned within an output .csv file, which is read by the Building Energy Management System to apply the control action.
- The real system operation of the Cona Hospital (e.g. on-off of all plants, fuel mass, production of electricity and heat) has to be passed from the Building Energy Management System to the computer in form of a .csv file with the datetimes. This allows the algorithm to preprocess and derive the necessary data from the plants correctly.
- The last available ShoTS and LoTS results are saved in two specific .csv files with the corresponding datetimes. In this way, in case of an algorithm failure, the solution available from the previous time-step can be used. This improves the control resilience with respect to failures.

4. Conclusions

In this report, the activities of the last task of WP2 are reported. The control algorithm for small scale district heating and cooling networks and multi-energy systems in general were developed. Firstly, the general concept of the control architecture was described. In order to comply with the goal of the WP2, which aimed to produce and algorithm able to control the system with multiple time scales, the control problem was divided into different subproblems. In particular, the control of the thermal power station was achieved through two interacting optimization levels. The Long-Term Supervisory (LoTS) module, assessed as an yearly scheduling Linear Programming problem, performed the scheduling of the daily energy produced by the plants over the entire year. The solution was passed to the Short-Term Supervisory (ShoTS) module, in order to provide additional long-term constraints to the ShoTS high-detail unit commitment problem. Both modules were Model Predictive Controllers, updated and repeated with daily and 15-minute time-steps. The control variables, required data, disturbances, constraints and cost function were reported for both modules in order to provide all necessary details for understanding the algorithm development. The communication between the modules and block diagram of the control protocol were also reported. Finally, the procedure for the implementation in the simulation environment setup in T2.2 but, most importantly, in the real test site identified in T2.1 was illustrated. In particular, the algorithm was firstly written in MATLAB and then translated in Python for the application to the test site. Specific attention was paid to the software specifications for this implementation, which regard the necessary files with parameters, forecast of disturbances and results that must be passed between the algorithm and the real system.

The output of the task is a complete Model Predictive Control protocol with two interacting optimization levels with both long and short time horizons. The algorithm will be tested in simulation environment through the simulation platform developed in T2.2, and in the real case study in WP3.

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