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Virtual testbed for model predictive control development in district cooling systems

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ABSTRACT

Recently, with increasing cooling demands, district cooling has assumed an important role as it is more efficient than stand-alone cooling systems. District cooling reduces the environmental impact and promotes the use of renewable sources. Earlier studies to optimise the production plants of district cooling systems were focused primarily on plants with compressor chillers and thermal energy storage devices. Although absorption chillers are crucial for integrating renewable sources into these systems, very few studies have considered them from the cooling perspective. In this regard, this paper presents the progress and results of the implementation of a virtual testbed based on a digital twin of a district cooling production plant with both compressor and absorption chillers. The aim of this study, carried out within the framework of INDIGO, a European Union-funded project, was (i) to develop a reliable model that can be used in a model predictive controller and (ii) to simulate the plant using this controller. The production plant components, which included absorption and compressor chillers, as well as cooling towers, were built using the equation-based Modelica programming language, and were calibrated using information from the manufacturer, together with real operation data. The remainder of the plant was modelled in Python. To integrate the Modelica models into the Python environment, a combination of machine learning techniques and state-space representation models was used. With these techniques, models with a high computational speed were obtained, which were suitable for real-time applications. These models were then used to build a model predictive control for the production plant to minimise the primary energy usage. The improvements in the control and the resultant energy savings achieved were compared with a baseline case working on a standard cascade control. Energy savings up to 50% were obtained in the simulation-based experiments.

1. Introduction

The building sector accounts for 36% of global energy use [1] and 28% of the global energy-related CO_2 emissions worldwide [2]. The use of energy for space cooling has increased faster than for any other end use in buildings during the past years [3]. This growth in the cooling demand is expected to keep rising in the future as well [4]. Currently, the role of district cooling (DC) systems is crucial in this sector as they offer a higher efficiency than stand-alone on-site systems. This is owing to the concentration effect of cooling loads [5] and higher efficiency of the water cooling process of DC systems compared to that of the air cooling process used in most stand-alone cooling systems [6]. Moreover, DC-based solutions are more flexible in coping with variable loads. They have a greater saving potential in peak-periods and can reduce environmental impact as compared to the stand-alone solutions. This is because, the former can reduce greenhouse gas (GHG) emissions as well [7]. Another important advantage of DC systems is that they can integrate renewable energy sources, such as solar or geothermal energy [8], and waste heat, easily, although further technological developments are required to reduce their cost and promote their penetration [9].

The European Union (EU) has set a target of promoting DC systems and conducting studies to maximise the efficiency of these systems [10]. Within INDIGO,[1] a Horizon 2020 EU-funded project, an improved management strategy has been defined for DC systems with the aim of reducing the primary energy use and maximising the system efficiency

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Nomenclature

a	Coefficient of matrix A
A	State matrix of state–space model
b	Coefficient of matrix B
B	Input matrix of state-space model
C	Heat Capacity, [J/K]
d	Disturbances of the problem
G	Thermal conductance, [W/K]
l	Term of the cost function
$\dot{m}$	Flow rate of the system, [m^3/h]
n	Dimensionality of variables, number
na, nb	Orders of ARX model
nk	Delay of ARX model
N	Prediction horizon
P	Power, [W]
r	References of the problem
s	Slack variables of the problem
$\mathscr{S}$	Feasible subset of s
t	Time instant
T	Temperature, [°C]
T_s	Sampling time
u	Inputs of the problem
$\mathscr{U}$	Feasible subset of u
V	Volume, [m^3]
x	States of the problem
$\mathscr{X}$	Feasible subset of x
y	Outputs of the problem

ABBREVIATIONS

ARX	Autoregressive with exogenous input
CCHP	Combined cooling, heating, and power
COP	Coefficient of performance
DC	District cooling
DCOL	District cooling open-source library
DH	District heating
DHC	District heating and cooling
EU	European Union
GHG	Greenhouse gas
HVAC	Heating, ventilation, and air condition
HX	Heat exchanger
LTI	Linear time invariant
MIMO	Multiple-input multiple-output
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
MPC	Model predictive control
MSL	Modelica standard library
NLP	Non-linear problem
NLTI	Non-linear time invariant
NTU	Number of transfer units
PI	Proportional-integral
SS	State–space
TES	Thermal energy storage

GREEK LETTERS

α	Weighting factor in the cost function

SUBSCRIPTS

abs	Absorber
amb	Ambient
arx	ARX model
Ch	Chiller
con	Condenser
cons	Electrical consumption
D	Distribution (connection with distribution network inlet or outlet)
eva	Evaporator
gen	Generator
i	Number of the referred chiller
in	Inlet
k	Controller step
0	Initial
out	Outlet
ret	Return
Sto	Storage
th	Thermal consumption
tot	Total

SUPERSCRIPTS

pred	Prediction
set	Set-point

[11]. This strategy involves developing an advanced controller that optimises the operation of the production plant.

1.1. Review of operational optimisation of district cooling production plants

Until now, energy efficiency optimisation in cooling systems has been studied primarily at the building level. Advanced techniques have been tested to control the heating, ventilation, and air conditioning (HVAC) systems of buildings. Among these, model predictive control (MPC) has been touted as one of the most predominant and powerful control methods, as it considers disturbance predictions, exploits the building thermal mass, takes into account electricity price, and calculates the optimised control [12]. In the case of DC production plants, similar approaches have been attempted to a limited extent.

The operation of DC production plants, in most cases, is based on classical control methods, with planning or sequencing strategies applied in a non-automated manner [13]. These strategies strongly depend on the control designer and the operator's knowledge of the plant. More novel methodologies based on advanced predictive controllers have yielded important benefits in energy and monetary savings [14]. These predictive techniques anticipate the energy demand and allow scheduling of the energy production accordingly [15]. Highlights the significance of working with cooling load predictions to control DC systems and conducting further studies on the control of the chillers plants, their coordination with the thermal energy storage (TES), and the interaction with the users. Some of the most important studies are reviewed below.

So far, most of the studies, which have focused on DC production plant optimisation, have considered only the compressor chillers [16]. Formulated an optimal control problem for a cooling system with TES and two chillers, without explicitly using the structure of an MPC, but working with a perfect weather forecast. It demonstrated a significant saving potential in the utility cost and on-peak electrical demand [17]. Estimated the optimal number of compressor chillers needed in a DC plant and the associated savings potential. In Ref. [18], an MPC to schedule a production DC plant with compressor chillers and a TES was developed using mixed integer linear programming (MILP), and demonstrated good performance within an acceptable computational time for its application [19]. Optimised the operation of a DC plant with three water-cooled compressor chillers by using a combination of a genetic algorithm and MILP. In Ref. [20], the optimal operation of a DC plant with compressor chillers and a TES was calculated for a whole year, and guidelines were defined for the operation of these systems for different periods of the year [21]. and [22] used the Modelica computer programming language to model DC production components, namely fast response compressor chillers and TES. These models were calibrated based on real data and then reduced to look-up tables. This procedure successfully produced reliable models for MPC applications. Subsequently [21], showed improvements of approximately 20% in the overall coefficient of performance (COP) of the plant. Some other related studies can be found on the optimisation of multi-chiller plants placed directly on buildings instead of being used as a component of a DC. This was the case with [23], which used particle swarm optimisation algorithms to study the effect of different optimisation approaches for the sequencing of chillers and the supply conditions in a multi water-cooled compressor chiller plant with different performance curves. They obtained savings of up to 13.6% in the total energy consumption corresponding to a simulation of two days [24]. Presented a real-time optimisation of a plant with two chillers, focusing on the enhancement of the supply conditions. In Ref. [25], a predictive chiller control for scheduling was developed using data-driven models, which achieved an average performance increase of 20%.

The compressor chillers are widely used, as their COP is 4.7–5.4 compared to absorption chillers, which have a COP of 0.7–1.3 [26]. However, a remarkable advantage of absorption chillers is that they can use renewable energy sources such as biomass, solar, or geothermal [27]. This reduces not only their dependency on fossil fuels, but also their own GHG emissions [28]. The absorption chillers are also used in combined cooling, heating and power (CCHP), also known as trigeneration [29]. The use of CCHP was highlighted in Ref. [30] as having achieved significant reduction in CO_2 emissions. Furthermore, it was stated that the cost-effectiveness of CCHP systems would rely on electricity production. These systems are more widely used in heating-dominated areas, where the role of the cooling system is supplementary. On the other hand, in cooling dominated areas they are not so common because their efficiency becomes lower when the aim is to provide a cold climate [15]. Ref. [31] mentioned the importance of further integrating renewable energy sources and CCHP to reduce fossil fuel dependency, minimise GHG emissions, and improve system stability and efficiency. In the same direction [32], also stated the importance of system operational enhancement with regard to absorption chillers.

As for the optimisation of these systems [33], focused on the optimisation of a CCHP plant using black-box models for the main components and performing a simulation over one day [34]. studied a micro-CCHP operation optimisation with the aim of obtaining a guiding principle. In Ref. [35] a district heating and cooling (DHC) system's operation was optimised using a simplified model of the plant, considering a whole year with an hourly sampling, and obtained a direction on how the plant should be run [36]. looked for the economic and environmental optimisation of a CCHP [37]. reported on the optimisation of a CCHP powered by solar energy for annual operation study. With regard to the feasibility study of different chillers technologies [38], investigated a DC production plant with both absorption and compressor chillers by developing an integrated multi-period optimisation model and showed that economic profits could be achieved when optimal operation was simulated.

1.2. Limitations of existing studies

From *Section 1.1*, it can be found that most of the studies on DC production plants were focused on plants with only compressor chillers [16–20]. In these studies, the systems utilised the inertia introduced by the TES, which contributed to economical savings and flexibility [39]. However, these studies modelled chillers ideally, without considering their dynamics, and assumed that there was no tracking error between the controlled variables and the references. This approach could be suitable for plants which have only vapour-compression chillers with very fast dynamics; however, it would lead to time-response problems with slower chillers. This is the case with hybrid plants with **absorption** chillers. These chillers face a lengthy delay before reaching the desired capacity. This is due to two characteristics of these systems: (i) the heat input to the system, whether from steam, gas or solar thermal sources, is regulated with only a single-capacity valve, and (ii) the cooling production system is chemical-based [40].

Absorption chillers were considered in some studies on CCHPs [32–37], in which the main purpose was not cooling; therefore, the components related to cooling technology were neither modelled nor analysed in detail [15]. commented on the importance of further research in CCHP for cooling requirement dominated areas, as very few studies are currently available. Moreover, most studies optimised the operation for an entire year with daily discretisation, to provide certain general guidelines regarding operation.

Thus, there is a lack of research with a real-time application approach that aims to develop a predictive controller to optimise a DC production plant with different chiller technologies (compressor and absorption chillers), considering the detailed dynamic behaviour of these technologies. Accordingly [41], highlighted the importance of studying coupled thermal and electrical production with respect to chillers.

1.3. Objectives of this study

The main objective of this study is to develop a testbed for a production plant of a DC, for building a predictive model to be used by an MPC. The model used by the MPC must comply with the following requirements:

1. It should be descriptive enough to capture the most significant dynamics of the real components, noting that these systems combine both fast and slow dynamics, as well as different multi-physics behaviours.
2. It should be computationally economical because the optimisation problem to be solved by the MPC optimiser may entail a large amount of computation.

As for the first requirement, Modelica, which is an object-oriented programming language, is suitable as it can manage complex systems and simulate dynamics [42]. It was previously used to model absorption chillers ([43,44]), as well as compressor chillers ([45]). However, Modelica models are usually computationally expensive. Therefore, detailed models in Modelica are reduced by applying machine learning techniques. This approach was successfully applied in Ref. [21,22], although with compressor chillers. Similar approaches for absorption chillers have not been found in the literature.

Moreover, this study also aimed to simulate the developed MPC to maximise the efficiency of a production plant and compare its performance with a baseline case involving a cascade-based control operation. The energy savings and improvements in the control, which were achieved with the MPC, were estimated through a comparison with the baseline case.

Considering the limitations of existing studies mentioned above, this study provided a production plant model with both absorption and compressor chillers. Moreover, the procedure to develop the specific component models ensured that the dynamic characteristics of each type of chillers were adequately represented.

Compared to most of the studies of operational optimisation, this study developed the strategy of operation through a controller designed to be used in real-time in the plant and operating with a short control period (5 min).

1.4. Organisation of this paper

Firstly, the method followed in the study is presented in Section 2.

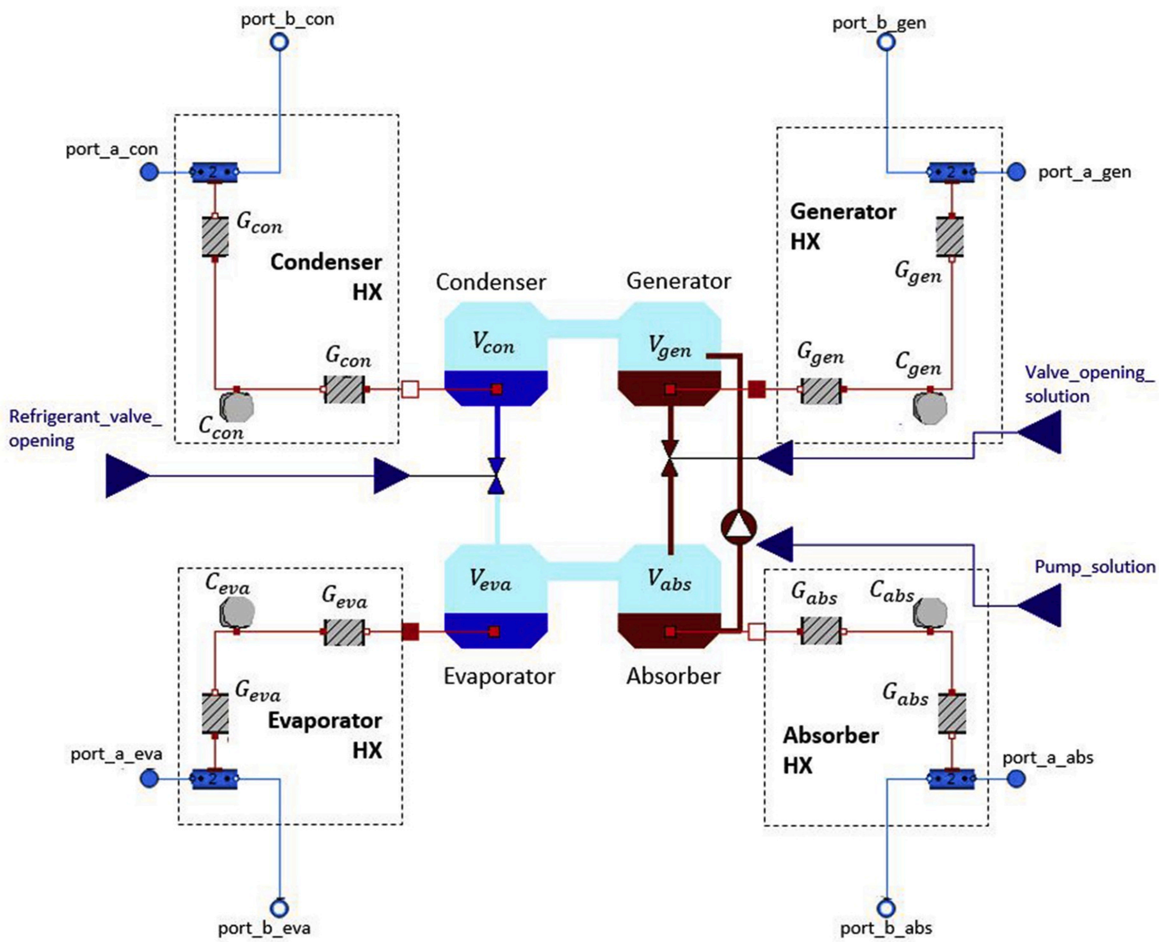

Fig. 1. Model of the absorption chiller built in Modelica from DCOL.

The main characteristics of an MPC are reported in Section 2.1; the detailed and reduced models developed for the chillers are presented in Section 2.2; the model for the whole production plant is shown in Section 2.3; and the MPC developed for the aforementioned system is introduced in Section 2.4. Next, the main results obtained in the study are presented in Section 3, together with a discussion and analysis of the same. Finally, Section 4 reports the main conclusions of the study.

2. Method

All the developments involved in the design of the MPC for the production plant are presented in this section. Firstly, the fundamentals of MPC are briefly introduced. Next, the models developed for the chillers and the entire production plant are described. Finally, the production plant's MPC and its characteristics are presented.

2.1. Model predictive control

MPC is an advanced control method, in which the control strategy is defined by minimising an objective function based on the dynamics of the plant. MPC operates with a receding finite horizon and, typically, discretised time. When provided with a reliable model of the plant, it is a powerful control technique that anticipates future events and controls the system based on the model predictions. Usually, even if the control actions are calculated for all the predictions of the MPC horizon, only the first control action is applied to the real plant and the optimisation problem is solved at every time step [46].

The MPC can be represented by an optimal control problem, as described in [47]:

$$\min_{u_0,\dots,u_{N-1}} \ell_N(x_N) + \sum_{k=0}^{N-1} \ell_k(x_k, y_k, u_k, r_k, s_k) \tag{1a}$$

$$s.t. \quad x_{k+1} = f(x_k, u_k, d_k), \quad k \in \mathbb{N}_0^{N-1} \tag{1b}$$

$$y_k = g(x_k, u_k, d_k), \quad k \in \mathbb{N}_0^{N-1} \tag{1c}$$

$$s_k = f(x_k, u_k, d_k), \quad k \in \mathbb{N}_0^{N-1} \tag{1d}$$

$$x_k \in \mathscr{X}, \quad k \in \mathbb{N}_0^{N-1} \tag{1e}$$

$$u_k \in \mathscr{U}, \quad k \in \mathbb{N}_0^{N-1} \tag{1f}$$

$$s_k \in \mathscr{S}, \quad k \in \mathbb{N}_0^{N-1} \tag{1g}$$

$$d_k = d(t + kT_S), \quad k \in \mathbb{N}_0^{N-1} \tag{1h}$$

$$r_k = r(t + kT_S), \quad k \in \mathbb{N}_0^{N-1} \tag{1i}$$

$$x_0 = x(t) \tag{1j}$$

$x_k \in \mathbb{R}^{n_x}$ represents the values of the states of the problem; $y_k \in \mathbb{R}^{n_x}$ represents the outputs; $u_k \in \mathbb{R}^{n_x}$ represents the inputs; $d_k \in \mathbb{R}^{n_x}$ represents the disturbances; $r_k \in \mathbb{R}^{n_x}$ represents the references; and $s_k \in \mathbb{R}^{n_x}$ represents the slack variables. All of them correspond to the k-th step, with N being the horizon length with a sampling time T_s. n represents the dimensionality of each variable [47].

The objective function, expressed in Eq. (1a) has two terms, the terminal penalty $\ell_N(x_N)$ and the stage cost $\ell_k(x_k, y_k, u_k, r_k, s_k)$. The latter assigns a particular cost to each variable. At each step k, the predicted state values are obtained from the state update Eq. (1b), while the predicted outputs are obtained from the output Eq. (1c). The slack values, representing algebraic equations among the inputs, states and outputs, are included as additional constraints in Eq. (1d). The states, inputs, and slacks should belong to the corresponding feasible subsets $\mathscr{X}$, $\mathscr{U}$, $\mathscr{S}$ of $\mathbb{R}^n$, which are included as constraints, expressed using Eq. (1e), Eq. (1f), and Eq. (1g), respectively. Eq. (1h) and Eq. (1i) represent the initialisation of the disturbances and references for the whole prediction horizon, and Eq. (1j) represents the initial conditions for the state variables.

2.2. Chiller models

Models of different types of chillers, namely air-cooled and water-cooled compressor chillers, and absorption chillers, were developed within the INDIGO project. Firstly, detailed models were built using Modelica. These models were then reduced using machine learning techniques, which allowed for the implementation of the models in the development environment of the MPC (Python, in this study).

2.2.1. Modelica models for the chillers

Both absorption and compressor chillers were modelled using the *Generation package* of the district cooling open-source library (DCOL) [48], developed within INDIGO. They are parametric thermo-fluid dynamic models. Moreover, models of an open and a closed cooling tower were developed, to be integrated with the models of the water-cooled chillers.

2.2.1.1. Absorption chiller Modelica model. The model was based on an absorption cycle-based chiller with aqueous lithium-bromide (LiBr + H_2O) as the refrigerant solution. The properties of the solution were defined using [49] as reference, in which the generic thermodynamic properties of LiBr + H2O were presented. In addition [50], was referred to for the properties at higher temperatures corresponding to the operation temperatures of the triple effect absorption chillers [51]; was consulted for the values of specific enthalpy, entropy, and heat capacity over a wide range of temperatures; , and [52] was used for the models and equations for other thermodynamic properties. The configuration of the absorption chiller model is shown in Fig. 1.

The model consisted of four volumes representing the Condenser (V_{con}), Generator (V_{gen}), Evaporator (V_{eva}), and Absorber (V_{abs}). These volumes comprised the **absorber generator vessel** and the **evaporator condenser vessel**, which considered two media (liquid and vapour) that would be in equilibrium with mass and energy balance. Each volume would be connected to a heat exchanger (HX) represented by two thermal conductors with thermal conductance G, a heat capacitor with capacity C (both of which were assumed constant and were model parameters), and a dynamic pipe.

The control signals included in the model were the openings of the refrigerant valve (*Refrigerant_valve_opening*) and chilled water valve (*Valve_opening_solution*), and the signal for the pump of the absorber generator vessel (*Pump_solution*). The inlet and outlets of each pipe of the system were represented by *port_a* and *port_b*, respectively. In addition, the flow was assumed to be laminar.

2.2.1.2. Compressor chiller Modelica model. A physics-based model based on a typical vapour-compression cycle was used to model a compressor chiller. The structure of the model is represented in Fig. 2.

This model was constructed by integrating four main components, namely a compressor, condenser, thermal expansion valve, and

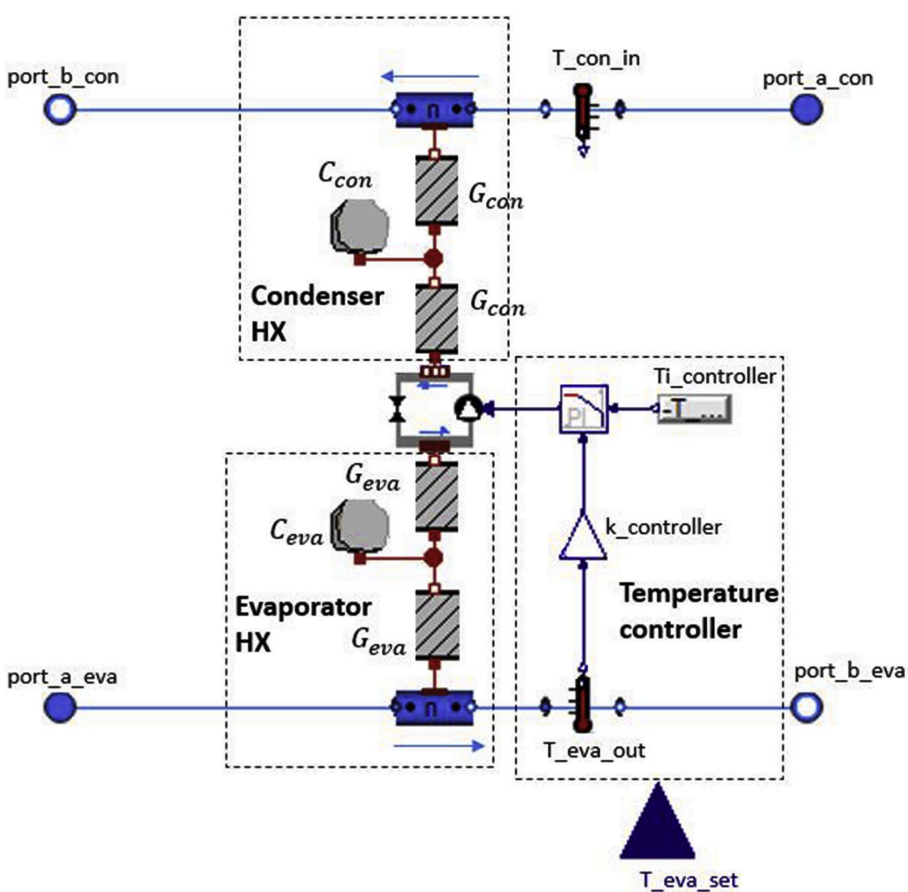

Fig. 2. Model of the controlled compressor chiller built in Modelica from DCOL.

evaporator. These component models were directly taken from the Modelica standard library (MSL). The compressor model was based on the model of a controlled pump. Both the condenser and evaporator were represented together with a heat exchanger, modelled by two thermal conductors of conductance *G*, thermal capacitor *C*, and the model of a dynamic pipe, The inlet of the pipe was represented by *port_a* and the outlet by *port_b*.

The vapour compressor system model included a proportional integral (PI) controller, which would modulate the compressor power; therefore, the temperature of the outlet water at the evaporator would match a set point given as an input (*T_eva_set*). The gain of the PI is *k_controller* and the time constant of the integrator block is *Ti_controller*. Moreover, another PI controller was included to emulate the feedback loop, which would control the evaporator outlet temperature, actuating on the expansion valve; however, this controller was not amenable to parameterisation.

2.2.1.3. Counter-flow open cooling tower Modelica model. This model represents a completely open cooling tower, as shown in Fig. 3.

The air was blown from the lower part through the tower, and it cooled the water sprayed at the top of the tower. The inlet flows of air and water were represented by the inlets *port_a_air* and *port_a_water*, respectively, and the outlet flows by *port_b_air* and *port_b_water*, respectively. Both sensible heat (owing to the increase of the air temperature) and latent heat (owing to the evaporation of part of the water) were transferred.

The chilled water was stored in a basin at the bottom of the tower. The heat loss through the storage wall from the floor was represented by *port_a_floor*, and the heat loss to the surroundings was denoted by *port_a_ambient*. The water basin was characterised by parameters related to its dimensions. The level of the tank was obtained as an output of the system. An overflow water fluid was included (*port_a_Owater*).

Some references from the earlier studies were used to build the model. Among these references, [53] presented a generic and universal model for cooling towers that could be used for the counter-flow case [54]; developed a model that considered, in detail, the dynamics of the counter-flow cooling towers; and [55] included a detailed method to obtain an equation for the performance of the cooling tower.

The main assumptions of the model were as follows:

- A part of the water flow is evaporated during the cooling process.
- The pressure drop of the air is considered.
- All the heat is transferred from the water to the air; i.e., heat losses during the water cooling are not considered.
- The number of transfer units (NTU) is used to calculate the amount of heat transferred from the water to the air. The design parameters of the tower need to be defined in the model.

2.2.1.4. Counter-flow closed cooling tower Modelica model. This model represents a completely closed cooling tower, as shown in Fig. 4.

In this case, both sprayed water and air were used to cool the fluid flowing through the pipe in the tower. The inlet and outlet of the air fluid were represented by *port_a_air* and *port_b_air*, respectively, and those of the cooling water by *port_a_Cwater* and *port_b_Cwater*, respectively. The sprayed water would extract heat of the chilled fluid, when it was in contact with the external layer of the pipe; at the same time, the air was heated when it was in contact with the sprayed water (i.e., sensible heat and latent heat are transferred to the air).

As in the case of the open cooling tower, a water basin was included, in which the heat losses to the surroundings (*port_a_ambient*) and to the

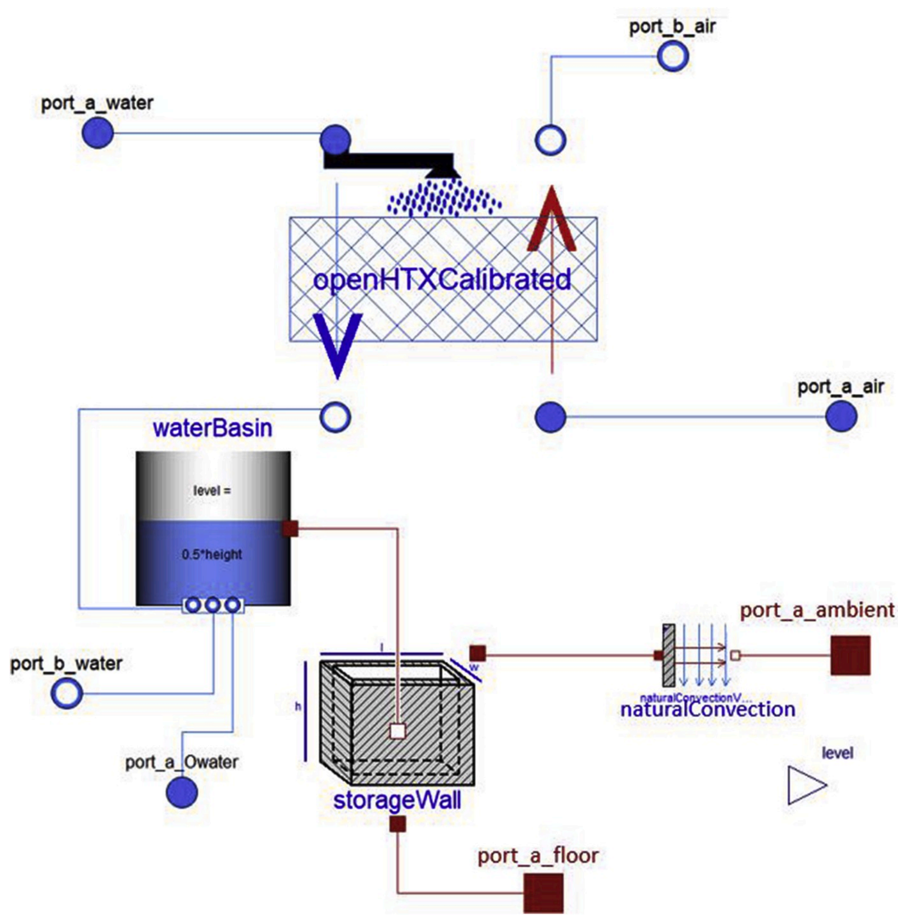

Fig. 3. Counter-flow open cooling tower model in Modelica from DCOL.

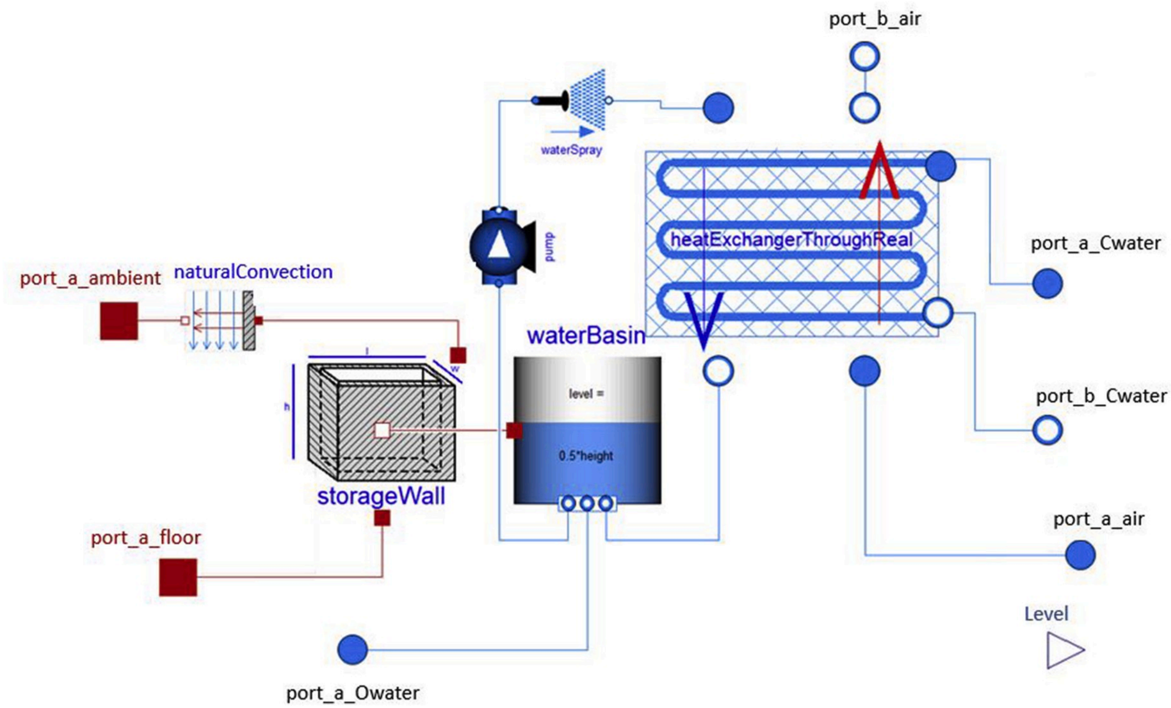

Fig. 4. Counter-flow closed cooling tower model in Modelica from DCOL.

floor (*port_a_floor*) were integrated.

The same assumptions as for the counter-flow open cooling tower in *Section 2.2.1.3* were made, in addition to the following:

- The chilled fluid flows through a pipe.
- The pressure drop of the chilled fluid is also considered.

2.2.2. Inputs and outputs of the models of the chillers

The inputs and outputs considered for the required models depend on the chiller type, and these are shown in Table 1.

2.2.3. Machine learning techniques to build reduced models

The models from Modelica were used as data generators to train machine learning algorithms, which were computationally more economical and still captured the necessary dynamics for the MPC. The machine learning techniques used in this study are explained below.

Calibration of the detailed models: The models created in Modelica were calibrated with the datasheets of each chiller provided by the manufacturer, together with data obtained from the test-site. The different parameters of the system were defined according to these data.

Virtual data generation: Once the Modelica models were calibrated, a set of virtual experiments were conducted to generate virtual data for each chiller. The inputs of the model were varied randomly across their valid ranges and with the frequencies expected in a real system, following the Latin hypercube sampling method. This would allow characterising the system over the whole input space, which would not be possible if real data were used directly (defined by operating conditions).

Autoregressive with exogenous input (ARX) model identification: Different types of complex models were tested; however, finally, linear estimators based on ARX architecture were used. They were identified using the least squares method, which was proven to be adequately accurate.

The resulting reduced models were multiple-input multiple-output (MIMO) ARX matrices. The models have the structure shown in Eq. (2a):

Table 1
Inputs and outputs for each chiller type model.

CHILLER TYPE	INPUTS	OUTPUTS
AIR-COOLED COMPRESSOR CHILLER	Outlet temperature set-point of chilled water T_{Gi}^{set} [°C]	Outlet temperature of the chilled water T_{Gi} [°C]
	Chilled water flow rate $\dot{m}_{Gi}$ [m^3/h]	Consumed electrical power $P_{cons\ i}$ [W]
	Inlet temperature of the chilled water T_{inG} [°C]	
	Inlet temperature of the cooling air (ambient temperature) T_{inAmb} [°C]	
WATER-COOLED COMPRESSOR CHILLER	Outlet temperature set-point of chilled water T_{Gi}^{set} [°C]	Outlet temperature of the chilled water T_{Gi} [°C]
	Chilled water flow rate $\dot{m}_{Gi}$ [m^3/h]	Consumed electrical power P_{consi} [W]
	Inlet temperature of the chilled water T_{inG} [°C]	
	Cooling water flow rate $\dot{m}_{con}$ [m^3/h]	
	Inlet temperature of the cooling water T_{inCon} [°C]TinCond	
ABSORPTION CHILLER	Outlet temperature set-point of chilled water T_{Gi}^{set} [°C]	Outlet temperature of the chilled water T_{Gi} [°C]
		Consumed thermal power P_{thi} [W]
		Consumed electrical power P_{cons} [W]

$$y(t) + a_1 \cdot y(t-1) + \ldots + a_{na} \cdot y(t-na) = b_1 \cdot u(t-nk) + \ldots + b_{nb} \cdot u(t-nb-nk+1) \quad (2a)$$

The orders of the ARX model are *na* (number of poles) and *nb* (number of zeros plus one). The delay of the system (number of input samples that occur before the input affects the output) is *nk*. The inputs of the system are *u*; the outputs are *y;* and *t* is the corresponding time instant. This structure can be written in a more compact form by using the ARX matrices [56].

$$y(t) = A_{arx} \cdot Y(t) + B_{arx} \cdot U(t) \quad (2b)$$

$$Y(t) = y(t-1) \ldots y(t-na) \quad (2c)$$

$$U(t) = u(t-nk) \ldots u(t-nb-nk+1) \quad (2d)$$

$$-A_{arx} = a_1 \ldots a_{na} \quad (2e)$$

$$B_{arx} = b_1 \ldots b_{nb} \quad (2f)$$

where A_{arx} and B_{arx} are the ARX matrices of the model; $a_1 \ldots a_{na}$ represent all the coefficients of the A_{arx} matrix; and $b_1 \ldots b_{nb}$, are the coefficients of the B_{arx} matrix.

A script was coded using Python to automatically generate the reduced models of the components from the virtually generated data.

State Space (SS) model representation: From the ARX matrices, the SS model representation was obtained, based on [57]. This representation was used in the MPC implementation in Python.

2.3. Production plant model

A model of the production plant configuration in the case study is presented. Next, the main assumptions of the model are enumerated. Finally, the baseline case used for the results analysis is introduced.

2.3.1. Production plant model based on the configuration of the test-site

The production plant considered for the study was based on the DC plant in Basurto Hospital in Bilbao (Spain), which is the test-site of the INDIGO project [58]. Four chillers were modelled, which included one absorption chiller and three compressor chillers. Each chiller has a dedicated pump to control the flow rate through itself. The hospital also has a district heating (DH) system, with cogeneration motors. The excess heat obtained from the cogeneration is used in the absorption chillers of the DC. The absorption chiller can be used only when there is available heat from the cogeneration. Moreover, the system also has a small TES, which is connected in parallel. The general configuration is shown in Fig. 5.

The variables represented in Fig. 5 are the outlet temperatures of the chillers (T_{Chi} stands for the outlet temperature of the i-th chiller), flow rate through each chiller $\dot{m}_{Chi}$, the consumed power by each chiller $P_{cons\ i}$, production outlet temperature T_{Ch}, return temperature to the production entering the chillers T_{retCh}, flow rate through all the chillers $\dot{m}_{Ch}$, TES outlet temperature T_{Sto}, TES flow rate $\dot{m}_{Sto}$, temperature supplied to the distribution network T_D, return temperature coming from the distribution network T_{retD}, distribution network flow rate $\dot{m}_D$, and the total delivered power to the distribution P_{Dtot} (to the consumers).

The types of chillers and their characteristics are specified in Table 2. The dynamics of the chillers were fixed by setting different values for the parameters in the Modelica model representing the inertia of the chillers.

To complete the model of the production plant, the corresponding mass and energy balances were included in the plant model equations. The plant has a TES consisting of a water tank. Owing to its reduced size, the tank has a very limited capacity to store cold water and hence, acts only as a buffer.

This TES was represented by a non-linear time invariant (NLTI) system that simulated the charging and discharging of the TES considering the capacity, thermal characteristics, and operating temperatures of the tank.

At each control period, the MPC would specify whether the TES was charging or discharging. Thus, the flow rate $\dot{m}_{Sto} > 0$ when the TES was discharging and < 0 when it was charging. Consequently, the resulting model for the production plant was non-linear. This switching behaviour of the TES (i.e., changing from one operation mode to another) was modelled using *CasADi*[1] operators without having to explicitly introduce hybridity into the optimisation problem.

The low-level controllers of the chillers and cooling towers would oversee their operation to ensure that the requested set-points of temperature and mass flow rate were achieved properly. The operation of this low-level control was compatible with the high-level control in the MPC.

In several MPC implementations, the on/off status of the chillers was represented by integer variables [9,10,13]. The drawback of introducing integers was that the resulting problem is a mixed integer non-linear programming (MINLP) problem, which is difficult to solve. In this

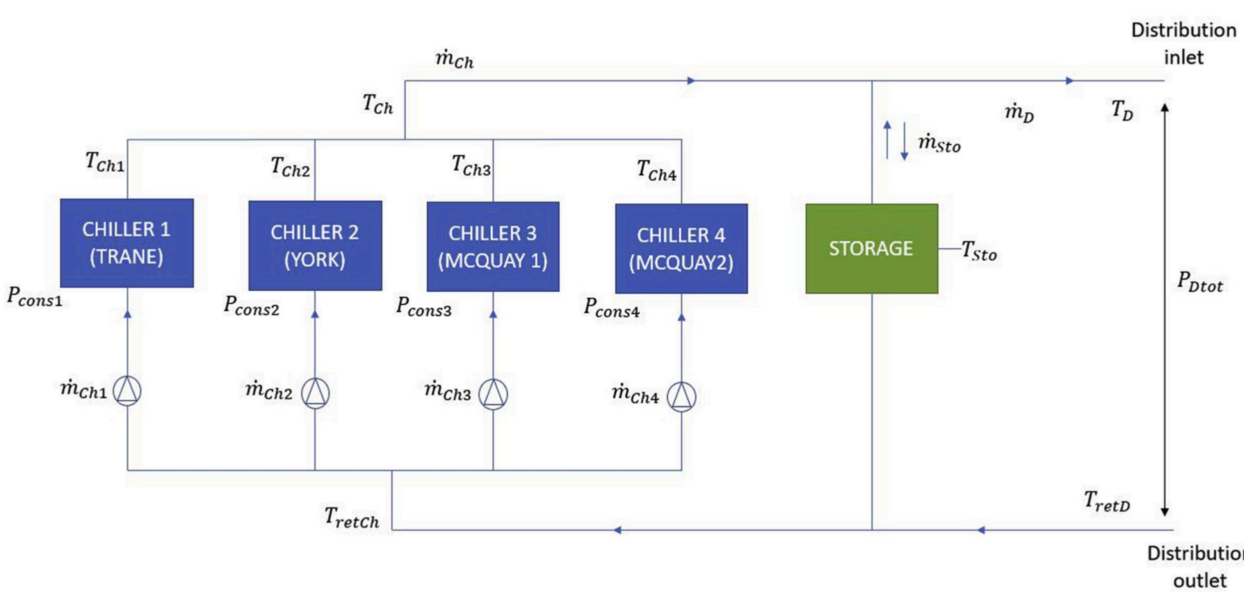

Fig. 5. Schematic of the production plant.

Table 2
Characteristics of the chillers from the production plant.

Model of the chiller	Type	Dynamics	Efficiency
York	Water cooled absorption chiller	Slow (~3 h)	High
Trane	Water cooled compressor chiller	Medium (~15 min)	Medium
McQuay 1	Air cooled compressor chiller	Fast (~5 min)	Low
McQuay 2	Air cooled compressor chiller	Fast (~5 min)	Low

study, the following assumptions were made to avoid integer variables:

- The charging/discharging operations of the tank were modelled with CasADi operators, as explained above.
- The chillers were not completely turned off; however, a minimum stand-by mass flow rate was established to ensure that the mass flow rate through the system would be a continuous variable.

Thus, a non-linear problem (NLP) was obtained, which was easier to solve.

2.3.2. Assumptions of the production model

The following assumptions were made in the model:

- The absorption chiller had infinite efficiency (i.e., the power consumption during its operation was considered to be nearly zero, as heat was available from cogeneration and because the electricity consumption of the chiller was negligible [59]).
- Heat was always available for the absorption chiller; thus, it had an infinite capacity.
- The chillers were set in the stand-by mode instead of being completely switched off, as is the norm in a real operation. A minimum stand-by mass flow rate would pass through the chillers when they were in stand-by mode with negligible power consumption.
- The pumps were modelled as ideal pumps (i.e., their losses and power consumption were considered to be negligible). It should be noted that their power consumption was low compared with the electrical consumption of the chillers for the test-site.
- The network return temperature was assumed to be well-controlled; therefore, it was limited between 12 and 14 °C.
- The ambient temperature, which was the system's main disturbance, randomly changed from 20 to 40 °C (three different values were taken during the entire simulation).

2.3.3. Baseline: cascade-based operation mode

As a baseline, a conventional cascade sequence was defined according to the actual operation in the test-site. The characteristics of the baseline operation were as follows:

- The sequence to turn on the chillers proceeded from the most efficient equipment to the least efficient one. As it was assumed that thermal energy was always available for the absorption chiller, this chiller was always the first one to be turned on.
- The criterion to decide how many chillers were to be turned on was based on some flow rate ranges for the demanded flow, as the chillers were currently operated in a real plant.
- The supply temperature set-point for each chiller was set to its nominal value.
- The flow rate through the chillers was fixed and was equal to its nominal value.

The MPC-based control strategy implies certain important changes that affect the way the plant was controlled in contrast to the baseline. These changes are as follows:

- There was no pre-defined sequence in which the chillers should be turned on. The MPC calculated the optimal combination based on the demand predictions and the model of the plant.
- The chillers worked at a variable supply temperature. The MPC calculated the optimal supply temperature of the chillers and the chillers temperature set-point changed accordingly.
- The mass flow rate through the chillers could also be regulated to ensure that the MPC would calculate the mass flow rate for each chiller.

Being able to change the supply temperature and mass flow rate conditions of the chillers allowed the plant to operate at a higher efficiency than in the case in which the cascade-based control was considered (i.e., with the imposition of fixed conditions). To guarantee these new set-points, low-level controllers consisting of PIs integrated in the chillers were used.

2.4. Production model predictive control

The MPC developed for the production plant is described in this section by presenting the input and output variables of the controller, the main objective of the controller, and its general structure.

2.4.1. Variables of the production model predictive control

The variables involved in the MPC resolution are shown in Table 3.

The consumption demand (from the buildings connected to the DC) was predicted by the simulation models. The supply conditions in the network were also assumed to be optimal. Both demand predictions and optimal network conditions were, respectively calculated by data-driven models and other controllers developed within the INDIGO project, and these are out of the scope of this study. Thus, the predictions that the MPC manages were the supply conditions at the inlet of the distribution network. These thermal conditions were defined by three independent variables, namely the total power demand in the network, supply temperature, and mass flow rate. It is important that the MPC would guarantee the thermal condition imposed by these variables, as this would influence the performance of the rest of the DC system.

The weather forecast was obtained through on-site measurements at Basurto Hospital and from the "C039 – Deusto" weather station of the Basque Agency of Meteorology.[2]

Table 3
Variables of the production MPC.

Inputs	On/off (standby) status of the chiller
	Outlet temperature of the chillers set-point T_{Gi}^{set} [°C]
	Flow rate of the chillers set-point $\dot{m}_{Gi}$ [m^3/h]
States	Outlet temperature of the chillers T_{Gi} [°C]
	TES temperature T_{sto} [°C]
Predictions	Predicted power demand in the distribution P_{Dtot}^{pred} [W]
	Predicted supply temperature at the distribution network inlet T_D^{pred} [°C]
	Predicted flow rate at the distribution inlet $\dot{m}_D^{pred}$ [m^3/h]
	Predicted ambient temperature T_{amb}^{pred} [°C]
Outputs	Supply power to the distribution P_{Dtot} [W]
	Supply temperature at the distribution inlet T_D [°C]

[2] http://www.euskalmet.euskadi.net/s075853x/es/meteorologia/estacion.apl?e=5&campo=C039.

2.4.2. Objective of the production model predictive control

The objective of the production MPC is to appropriately account for the energy while maximising the efficiency of the system.

Controlled operation: The desired distribution supply conditions that properly satisfy the energy demand were obtained using hard constraints imposed on the optimisation problem, which were as follows:

- The flow rate requirement at the distribution network was assumed to be fully satisfied by the flow rate from the chillers and the TES flow rate.
- The supply temperature to the distribution network was strictly constrained to have minimum deviations. The allowed error in the temperature can be fixed for the entire horizon or uniformly modified to ensure that only very small errors were permitted at the first horizon points; however, this constraint was relaxed for further points.
- As the return temperature from the distribution was known (from plant measurements), the power delivered would be achieved with only an error derived from the supply temperature error.

Optimised operation: The efficiency of the system was defined as the ratio of the power delivered to the power consumed by the plant. Thus, an optimised operation could be achieved by minimising the primary energy used by the chillers. This energy usage was included in the cost function (as a term that depends on the primary power consumption), together with the error in the supplied temperature to the distribution, and the variation in the temperature set-point (used to avoid large changes in the temperature requested to the chillers). The objective function including these terms is presented in Eq. (3).

$$\min \alpha_1 \sum_{t=0}^{N-1} T_D^{pred}(t) - T_D(t) + \alpha_2 \sum_{t=0}^{N-1} \sum_{i=1}^{n_G} P_{cons\ i}(t)$$
$$+\alpha_3 \sum_{t=1}^{N-1} \sum_{i=1}^{n_G} T_{Gi}^{set}(t) - T_{Gi}^{set}(t-1) \tag{3}$$

where T_D^{pred} is the predicted distribution temperature; T_D is the real temperature achieved at the distribution inlet; $P_{cons\ i}$ Pcons,i is the power consumed by the i-th chiller; T_{Gi}^{set} is the chiller outlet temperature set-point; N is the prediction horizon; n_G ng is the number of chillers in the production plant; and α_1, α_2, α_3 are, respectively the weighting factors for each term included in the cost function.

2.4.3. Structure of production model predictive control

To build the MPC, a single-shooting structure was used. The predictive model of the production plant was built from the production plant model shown in *Section 2.3.1*. All the constraints related to the limitations of the operation were included in the problem, and the production model was discretised. Next, a program was coded in *Python* language using *CasADi* [60] to define the model and the optimisation problem, which was solved by *Ipopt*.

3. Results and discussion

The results of this study comprise the results of the numerical verification of the models of the chillers and the results of the production MPC. A discussion of these results is presented below.

3.1. Results from the verification of the models for the test-site chillers

Fig. 6 presents the outputs of the simulation of one of the chillers, namely McQuay 1, which is an air-cooled compressor chiller. The chiller's outlet temperature and consumed power obtained with both the Modelica model (blue line) and the SS linear time invariant (LTI) model (red line) are presented. The simulation was performed for 24 h in both the cases, and they led to almost identical results. Similar results were obtained for the remaining chillers at the test-site.

3.2. Results from the production model predictive control

The production MPC and the baseline operation were simulated for several days with different loads taken from the real demand data. A representative day was selected to show the results clearly. Thus, the results included in this section correspond to a simulation of 24 h with a control period of 5 min and a prediction horizon of 4 h. White noise was introduced in the predictions to simulate any uncertainty (1–10%).

The plant currently operates at constant supply temperature, fixed at

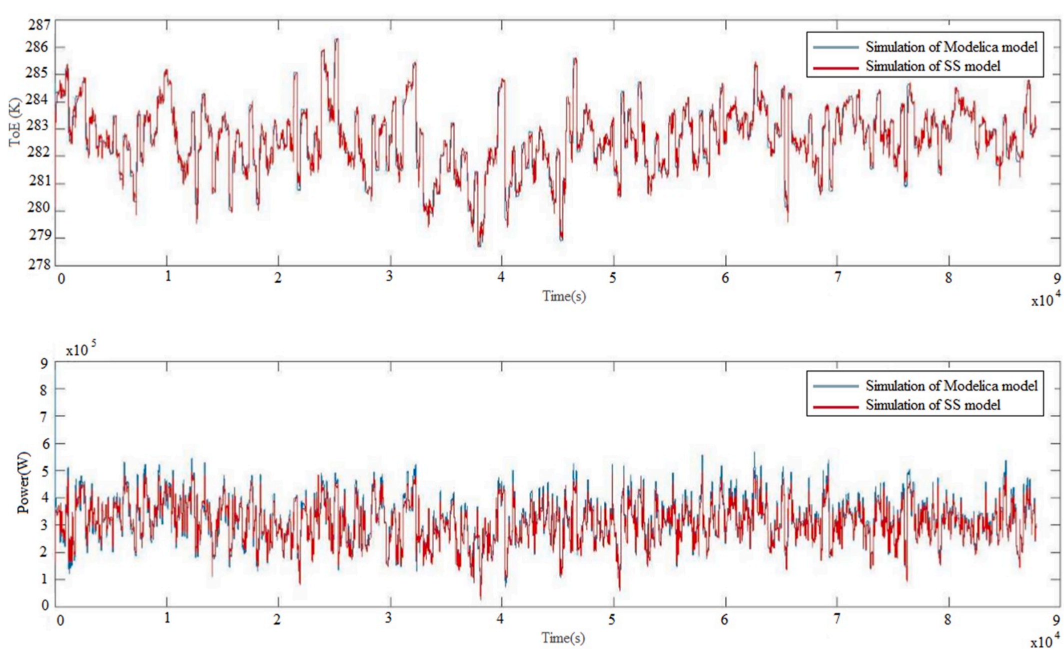

Fig. 6. Comparison of McQuay compressor chiller model simulation results with data from detailed Modelica model.

7 °C. The variation in the demand from the consumers was considered by defining a variable mass flow rate request to the production plant, as shown in Fig. 7. The maximum allowed error for the supply temperature was 0.1 °C in the whole horizon.

The supply temperatures for both the MPC and the baseline operation, along with the improvements achieved by the MPC, are shown in Table 4. The consumed power by the chillers in both operation modes and the energy savings achieved during the whole simulation time are summarised in Table 5. In both the cases, the Pandas[3] library for Python was used to calculate the mean, minimum, and maximum values; the standard deviation; and the 25th, 50th, and 75th percentiles from the

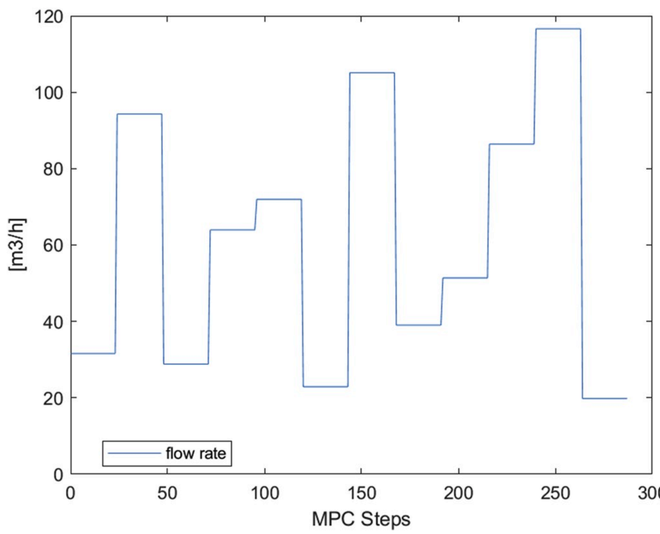

Fig. 7. Production mass flow rate demand during the simulation period.

Table 4
Supply temperature (Tout) with MPC and baseline operation, and improvements achieved.

Tout	MPC [K]	Baseline operation [K]	Improvements [%]
mean	280.15	279.32	81.30
std	0.02	0.22	22.72
min	280.06	279.14	−3.33
25%	280.14	279.20	80.32
50%	280.15	279.22	92.06
75%	280.16	279.28	93.90
max	280.24	280.10	98.59

Table 5
Power consumption with MPC and baseline operation, and energy savings.

Consumed power	MPC [W]	Baseline operation [W]	Savings [−]
mean	37864.27	80626.35	50.09
std	7082.52	28215.24	6.40
min	25666.09	41043.97	6.70
25%	32053.90	57604.91	50.97
50%	38088.89	74783.50	51.71
75%	44021.40	113404.93	52.50
max	59812.87	119131.54	54.10

[3] https://pandas.pydata.org/pandas-docs/stable/index.html.

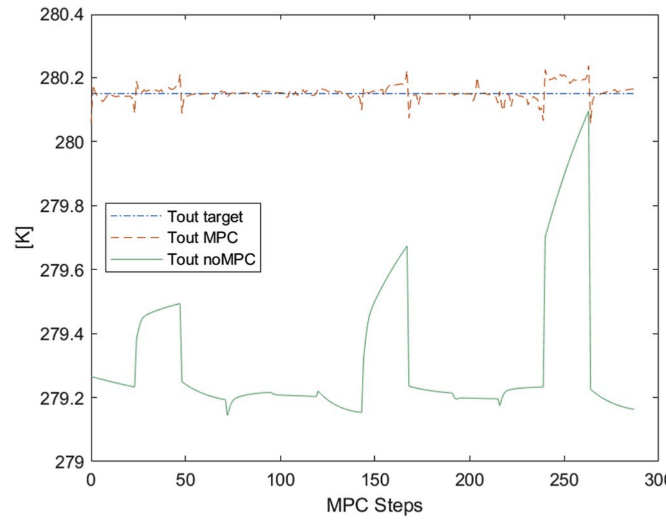

Fig. 8. Reference temperature, supply temperature with MPC, and supply temperature without MPC.

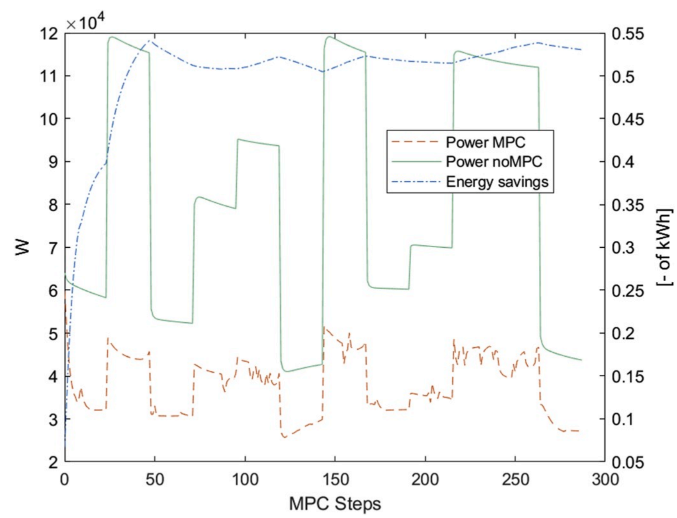

Fig. 9. Consumed power with and without MPC, and energy savings.

results of the simulation. The improvement in the supply temperature tracking was calculated as the ratio of the difference between the errors obtained without and with the MPC, to the maximum error without the MPC. The savings were obtained by calculating the difference between the power consumption without and with the MPC compared with the maximum power consumption without MPC.

A comparison between the two operation modes with regard to the supply temperature is shown in Fig. 8, and a comparison of the power consumption in Fig. 9.

3.3. Discussion

The MPC's performance depends significantly on the model's reliability. The production component models presented in this study were based on Modelica models that captured, in detail, the plant's dynamics. These models were reduced by generating synthetic data and applying machine learning techniques to calibrate data-driven ARX models, which were then transformed into an SS representation, thus obtaining computationally cheaper models. The reduced models performed similar to their Modelica counterparts. This provides an assurance of the reliability of the model for the controller.

The model reduction process presented in this study was verified only virtually. The next step with regard to this aspect would be the validation of the entire workflow of the reduction methodology in a relevant environment. This entails numerical validation of the reduced models, considering a real system's operational data directly.

Along with the validation of the reduction methodology, a thorough investigation on the impact of the prediction deviations (owing to data collection and modelling errors) in the MPC performance must be performed. As consequence of the proposed investigations, a further development should be the inclusion of a prediction error emulator into the testbed. This will provide a more robust tool for the development of an MPC for DC production plants by significantly increasing the reliability of the results obtained during the MPC development.

The use of the MPC improved the tracking of the desired temperature supplied by the production plant. Table 4 shows that this could be estimated from an 81% mean improvement using the MPC compared with the baseline scenario. Moreover, the standard deviation in the baseline case was higher than that in the MPC case, and the percentiles in the baseline scenario presented a greater difference. The MPC, in contrast, had a low standard deviation, and all the percentiles had very similar values. This means that the MPC, apart from having smaller errors in the tracking, was able to maintain them at low values during the whole simulation. In contrast, the baseline operation had points, in which the tracking error increased significantly compared to the mean error. Therefore, the largest improvements in the tracking could be seen at specific points. In the baseline case, comparing the errors in Fig. 8 with the demand in Fig. 7, it can be seen that the cascade actuation generated large errors when a significant demand increase appeared. In the case of small or moderate increases in the demand, the storage was able to cope with them; however, this was not the case with a high increase in the demand. One of the most meaningful reasons for the improvement with the MPC was the predictive capability of the controller, which allowed anticipating changes in the energy demand and scheduling the production to fit the demand better. This would be more relevant for systems with absorption chillers with slow time response, like the one presented in this research work. As for the small deviations on the MPC tracking, these could be owing to the uncertainty introduced in the predictions. As the demand used by the MPC was not the real one, errors appeared in the tracking.

The improvement of the temperature tracking of the outlet production temperature means that the conditions supplied to the distribution network could adjust the demand better and therefore, could also result in enhancements in other parts of the system. The desired supply temperature could be calculated to optimise the network distribution (i.e., the optimal supply conditions that would minimise the losses in the network) or ensure that the demand at each consumer was guaranteed. In these cases, obtaining the calculated temperature at the production outlet is essential to achieve the other objectives.

In the case of the energy savings, the mean value was estimated to be 50% in the performed simulations. In this case, the standard deviations for both the cases (with and without MPC) shown in Table 5 were higher, which meant that greater energy savings could be achieved at certain simulation points. The percentiles also demonstrated this point, and when Figs. 7 and 9 are compared, it can be seen that the biggest energy savings were achieved at greater demands, and that the energy savings were proportional to the demand. One of the key aspects in reducing the power consumption in the studied case was the use of the absorption chiller. As was explained in *Section 2.3.2*, the absorption chiller was always available and it was assumed that it did not consume any power; therefore, it is not only desirable to always use the absorption chiller, but also operate it suitably. In the baseline operation, this chiller was always the first one to be turned on; however, its operation point was fixed. In the case of the MPC also, it was decided to turn it on in the first case; however, furthermore, it would actuate over the mass flow rate and the supply temperature so that it could cover the predicted demand better. As for the compressor chiller, it would act in both the control scenarios as a back-up unit, as was explained in Ref. [15]; however, the way it was operated was different. The baseline operation would actuate them at fixed supply conditions and consequently, with a fixed efficiency. Nevertheless, the MPC would calculate the operation conditions, at which the efficiency was better, as this could reduce the power consumption as explained in Ref. [23]. Moreover, when the chillers were working at fixed operation points, the charging/discharging profile of the TES was fixed according to the energy demand. In contrast, controlling the mass flow rate of the chillers would allow for deciding how the TES was used, thus imparting flexibility to the system. In the case study, the TES was small, and the handling capacity was limited; therefore, only a "limited" flexibility was achieved. However, if larger TESs were available, the flexibility obtained would be very significant, and the TESs could also contribute to important economical savings [14]. Therefore, further studies should be directed towards the simulation of this production plant, by including a TES with a higher capacity. Implementing the option to have a variable mass flow rate and supply temperature was not exclusive to the MPCs; these improvements could also be integrated with other types of controllers. However, to optimally define their set-points, an optimisation-based solution should be used, as was the case with the MPCs.

4. Conclusions

This paper has presented the definition of detailed models based on real data of chillers installed in a DC plant, along with the design of an MPC to control the production plant. The conclusions drawn from each part of the developments are presented below.

4.1. Modelica use

Modelica was used to create detailed models of the absorption and compressor chillers and the cooling towers. Modelica enables describing complex systems with multi-physics behaviour and different dynamics. Thus, its results are suitable to model chillers, capturing all the main physical characteristics.

In addition, Modelica has an object-oriented approach that allows the reuse of the models. Thus, the chiller models can be used for other studies or applications with different operating conditions or characteristics, by merely modifying some parameters.

Finally, another remarkable advantage of using Modelica is that the models are built following the physical structure; therefore, they are easier to understand.

4.2. Machine learning techniques for Modelica model reduction

The detailed models in Modelica were reduced by applying machine learning techniques, which essentially involved calibration of data-driven ARX models based on data generated through Latin hypercube simulations.

The calibration processes based on data collected directly from the plant operation usually present some limitations. The available data are often limited and do not cover all the operational ranges of the variables. In addition, they can be difficult to obtain. The calibration method explained in this study presented some compelling advantages in this sense. The Modelica models can be used to generate virtual data to calibrate the models in the entire input space in a non-invasive manner.

Moreover, this methodology enables achieving simpler models that can be integrated into the MPC and can be used in real-time applications without being computationally very demanding. Through the validated models, the controllers developed can also be tested before being integrated in a non-invasive way and thus, can facilitate the testing phase.

Although only virtual verification was performed for the reduced models, the simulation results showed only small deviations from the detailed models developed in Modelica, indicating that the model reduction methodology followed in this research may be suitable for supporting the development and testing of MPCs for DC systems. Further investigations may be conducted to validate the performance of the reduced models in more detail, and analyse the possible deviations.

4.3. Improvements in the control with a production model predictive control

An MPC was developed to control the production of the DC. This type of controller can schedule the energy supply foreseeing the demand conditions. This is of special interest for components with slower dynamics, as their actuation time is considered when the energy supply is scheduled. This is the case with TESs and absorption chillers. Most of optimisation studies in the literature focused on the TES, with only a few considering the absorption chillers' dynamics. The MPC allows solving an optimisation problem, and in this study, the power consumption in the production plant was minimised.

A comparison of the performance of the MPC with a standard control based on a cascade sequence was made by simulating the same demand conditions on the plant and controlling them with an MPC and with the standard control. The relative error in the supply temperature showed that the MPC controlled the temperature better than the cascade-based operation. This was due to the capacity of the predictive controller to anticipate substantial changes in the demand. Moreover, the power consumed by the chillers was significantly reduced with the MPC, resulting in an average saving of 50% in the power consumption compared to the baseline operation.

Further research should be directed towards an investigation of other aspects that could be optimised with the MPC, such as the economical operation cost or the environmental impact of the production plant of the DC, by using the developed models and partially modifying the MPC.

Credit author statement

Laura Zabala: Investigation, Formal Analysis, Writing - original draft preparation. **Jesús Febres**: Methodology, Software, Validation, Writing - review & editing. **Raymond Sterling**: Supervision, Writing - review & editing, Funding acquisition. **Susana López**: Project administration, Conceptualization, Investigation, Funding acquisition. **Marcus Keane**: Supervision, Writing - review & editing, Funding acquisition.

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