Title	Model predictive control for efficient operation of district cooling generation
Author(s)	Mohammadi, Adeleh
Publication Date	2023-04-21
Publisher	NUI Galway
Item record	http://hdl.handle.net/10379/17739

UNIVERSITY OF GALWAY

Model Predictive Control for Efficient Operation of District Cooling Generation

By Adeleh Mohammadi

Supervisor:

Dr. Marcus M. Keane, College of Science and Engineering

Co-supervisor:

Dr. Raymond Sterling, R2M Solutions Spain

In fulfilment of the requirements for the Degree of Doctor of Philosophy

April 2023

Abstract

The market for District Cooling Systems (DCS) is increasing in Europe as well as other parts of the world due to climate change and higher demand for thermal comfort in the buildings. The DCS have come into attention for their role in the energy efficient operation of buildings and districts. Many attempts have been made to operate the District Energy Systems (DES) more efficiently; however, a change in the method of modelling, simulation and control can bring further improvements in the energy performance of DES. The DCS has its challenges including low temperature differentials at the generation level, and optimal operation of the overall system which require specific modelling and control techniques to overcome.

In this thesis, the literature is critically reviewed to find out the role of modelling and simulation with respect to DCS. As a result, the current shortcomings in modelling and control of DCS are investigated. Then, an integrated modelling and simulation framework is developed for energy efficient and optimal operation of DCS. The predictive control approaches have proved to be effective in the control of DES in recent years. The Model Predictive Control (MPC) algorithms are exploited in a virtual testbed to increase the energy efficiency of District Cooling Generation Systems (DCGS). This thesis was performed as part of the EU H2020 INDIGO (2016-2020) project; the testbed and data used in the implementation of this thesis are provided through EU H2020 INDIGO (2016-2020). Furthermore, the MPC solution is analysed mathematically to prove its performance. The virtual testbed for modelling and control of the DCGS is tested on the Basurto hospital building in Spain as a part of EU H2020 INDIGO (2016-2020) project; the results are compared to the current control setup in the DCGS of Basurto to show the effectiveness of the MPC framework in energy efficiency of the DCGS. The comparisons show a theoretical 30% decrease in energy use using the MPC implementation of this thesis on each chiller in DCGS while the desired temperature is achieved for thermal comfort.

Keywords: *Energy Efficiency, Optimal Operation, District Energy Systems (DES), District Cooling Systems (DCS), District Cooling Generation Systems (DCGS), Model Predictive Control (MPC).*

Contents

List of Abbreviations

AHU	Air Handling Unit
ARX	Auto-Regressive Exogenous
BMS	Building Management Systems
COP	Coefficient of Performance
CO_2	Carbon dioxide
DHS	District Heating System
DCS	District Cooling System
DCG	District Cooling Generation
DOF	Degree of Freedom
EER	Energy Efficiency Ratio
HVAC	Heating, Ventilation, and Air-Conditioning
IDCG	Integrated District Cooling Generation
KPI	Key Performance Indicators
MPC	Model Predictive Control
NN	Neural Networks
QP	Quadratic Programming

List of Figures

List of Tables

List of Equations

Declarations

This dissertation is the result of my own work, except where explicit reference is made to the work of others. It has not been submitted for another qualification to this or any other University.

Adeleh Mohammadi

Acknowledgement

The research leading to the results presented in this thesis has been developed in the framework of project INDIGO, which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 696098. This PhD is partly funded by SPHERE project.

I would like to express my utmost gratefulness to my supervisor Dr Marcus Keane, and Dr Raymond Sterling for guiding and supporting me through my PhD journey.

I would like to express my gratitude to the College of Science and Engineering of University of Galway as well as my colleagues at IRUSE group and Ryan Institute. I would also like to thank the members of my GRC for their advice and support.

I would like to thank all EU H2020 INDIGO (2016-2020) project partners and specifically the coordinator TEKNIKER for hosting me on research placement in their office in Eibar, Spain. I am also thankful to Veolia for providing the data of Basurto hospital for the case study of this thesis.

I dedicate this thesis to my parents Zahra and Taj Mohammad. Thank you for bringing me to this world. I am thankful to my whole family, sisters, brother, all my in-laws, and the little ones who come to this world and grew up while I was busy with my PhD.

I am extremely grateful to my husband Mohsen and my daughter Enya for supporting me to continue through the finish line even when it got tough at times.

I am thankful to my friends at Galway Tango, Development Perspectives, and the supportive Iranian community of Galway for keeping me entertained, motivated, supported, and accountable during my PhD journey.

“I Love you,

I am Sorry,

Please Forgive Me,

Thank You”

Ho’oponopono

1 Introduction

1.1 Energy Use in Buildings

The primary reason to develop the Heating, Ventilation, and Air-Conditioning (HVAC) systems is to construct buildings with high level of thermal comfort for human beings [1]. An assessment of the cost of air conditioning in buildings shows that the energy use is growing in Europe in the last decades [2]. The studies on energy efficiency reveals that 46% of the total worldwide energy use and 40% of total energy use in Europe is in the buildings [3], [4]. These buildings also contribute to 36% of carbon dioxide emission in the European Union [4].

Numerous studies have been conducted to construct and maintain energy efficient buildings [5],[6],[7]. A main goal of the research in this area is to reduce the CO_2 [8], [9] and greenhouse gas emissions, enhance thermal comfort in buildings, increase indoor air quality [10], minimize energy costs, and reduce energy use in any form. The energy efficiency goals are realized through state-of-the-art technologies in buildings such as District Energy Systems (DES). The DES has come into consideration for their high efficiency and economical costs in districts [11].

1.2 District Cooling Systems Growth

The history of DCS dates back to 1800s when plans were made to use underground pipes to distribute clean, cold air to buildings [12]. The Colorado Automatic Refrigerator Company was the first cooling company which was launched in 1889. Later, a large cooling system were established in the Rockefeller Centre in New York City and the United States Capital buildings. The first DCS in Europe was the district heating and cooling system of the La Defense office complex in Paris in 1967. Later in 1990s, DCS was developed in Scandinavia for example the DCS of the city of Stockholm [13].

In Europe, it is estimated that the installed cooling systems will increase by approximately 55-60% from 2010 to 2025 [2]. District cooling demand increase in Europe is shown in Figure 1. Studies show that the electricity peak loads appear in city centres and commercial areas, even in northern countries, during summertime [14]. A significant part of this energy use is in DCS [15]. The DCS has been pointed out by the EU Energy Efficiency Directive (EED) [16] as one of the important means for accomplishing the energy efficiency goal of reducing primary energy use by 20%.

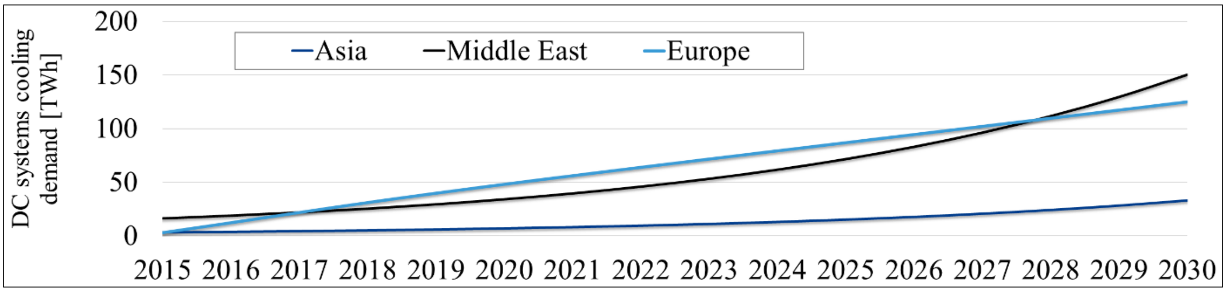


Figure 1: DCS demand increase (Retrieved from INDIGO project [17]*)*

The need for cooling has risen because of novel building designs, heat loads that are internal in the buildings, urban heat island effects, and thermal comfort issues. Further application of small-scale and distributed conventional air conditioners results in a substantial rise in peak electricity demand which turns into the need to have higher capacity electricity distribution systems operating at a lower efficiency [18]. Considering these consequences, DCS are being studied as they have the potential to offer solutions with 5 to 10 times higher efficiency compared to individual cooling systems. [18]. The decrease in building energy use through heating and cooling systems directly affects the amount of power and fuels being used, this makes the buildings more environmentally friendly.

1.3 DCS components

The DCS is composed of generation, distribution, and use sites (Figure 2). The generation site is where chilled water is produced in chillers and the heat is rejected through heat rejection circuits and cooling towers. The chilled water is then carried to the distribution system and through the pipelines to the consumption site and end-users. The consumption site consists of the Heating, Ventilation, and Air-Conditioning (HVAC) equipment in the buildings.

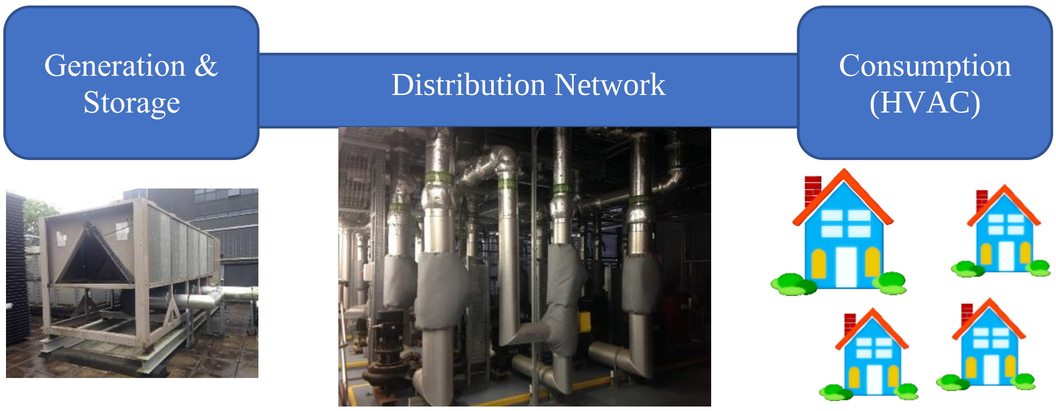


Figure 2: DCS Components (Photos taken from Alice Perry Engineering Building HVAC in NUIG)

1.4 Problem Statement

DCS offers higher efficiency compared to individual conventional cooling systems and has several other advantages in terms of reducing greenhouse gas emissions and space requirements. However, due to the costs of modification of existing DCS and corresponding built environment, there is great difficulty in achieving energy efficient operation of DCS with design optimisation. The basic issue is the fact that overall efficiency of DCS depends on the efficiency of its components. Besides, the efficiency of the components depends on how they are modelled and controlled based on the actual physical system and data. Thus, another method for maximizing the energy efficiency and minimizing the costs of already existing DCS is by means of control techniques using prediction models and actual data. However, the modelling and control techniques are studied separately in the literature but not as an integrated tool for DCS (The focus is on design optimisation rather than control optimisation [19]).

1.5 Research Question

The research question of this thesis is: *For existing District Cooling Generation Systems (DCGS), can an integrated modelling and control method be developed that*

- *Delivers required temperatures demand for thermal comfort*
- *And reduces the energy use?*

1.6 Objectives

This thesis aims to push the DCS Generation technology one step further by providing the integrated modelling and predictive control methods. The main objective of this research is the development of a more efficient DCS Generation by improving system modelling and control. This thesis contributes to the following key areas:

- The existing literature on DCS have been systematically reviewed. It's been found that there is not enough literature on enhancing DCS operation using MPC technologies. MPC is an advanced, well-developed method in the currently existing industry and academia; However, it is not exploited in DCS. The literature review process is where the gaps in modelling and control of DCS are identified and how these gaps affect the energy efficiency of DCS. By finding the gaps, a new strategy is proposed to integrate models with control and take advantage of the latest MPC technologies to achieve optimal and efficient performance of DCS.
- Research has shown that advanced building control techniques, including MPC, can

significantly reduce energy use and greenhouse gas emissions. Despite numerous research papers and several pilot installations, the adoption of this technology in the building market is still in its early stages. One of the main challenges facing the building sector is that engineers responsible for Building Management Systems (BMS) lack advanced education in modern optimal control methods and tools, unlike control engineers in other industries where MPC has been successful, such as the process industry. Furthermore, unlike the design and production of cars or electronic devices, building and HVAC system design and production are not standardized. Each building is unique and requires customized modelling and control design, which increases engineering time and cost, especially for advanced control strategies. In addition, a limiting factor is the inadequate information and communication technology (ICT) infrastructure in pre-existing buildings [20].

- This research is focused on providing optimal solutions for DCS Generation. These optimal solutions are based on *dynamic models and dynamic behaviour* of generation components; Therefore, the solutions allow for adaptive operation.
- Model Predictive Control (MPC) is used in the control of chilled water generation systems, i.e., chillers and cooling towers. This control approach has proved to be effective to handle the constraints of the system. In addition, the objective function of the optimisation problem includes energy efficiency objectives such as electricity use and thermal comfort in the control problem formulation.
- This study implements optimized predictive controllers for components to minimize cost or maximize energy efficiency while addressing the DCS challenges. To test the effectiveness of the methodology, the results are implemented on an existing hospital building in Spain in a real-life setting.
- The result of the thesis is an integrated DCS Generation modelling and control to facilitate the implementation of MPC on DCS. This methodology is applicable to any DCGS.

1.7 Thesis Outline

The chapters of the thesis are as follows:

- Chapter 1 – Introduction will focus on problem statement, research question, and the objectives of this thesis.
- Chapter 2 – The Background and Literature Review on DCS modelling and control, the importance, and the reasons behind studying DCS, and the possibilities for

improvement considering the current literature. The main purpose of this chapter is to critically review the current literature in DCS modelling and control and identify the gaps that needs to be addressed.

- Chapter 3 – Overview of the proposed methodology including the detailed description of prediction models of DCG, MPC of the generation system for chilled water, MPC problem formulation with energy efficiency objective, and obtaining a mathematical solution for the MPC problem using **optimisation algorithms**.
  - Preparation: Overall Engineering of DCG and the data collection
  - DCS Modelling: The application of modelling tools and techniques in generating a prediction model for the MPC of DCS
  - DCS Control: The use of MPC in improving energy efficiency of DCG, as well as the mathematical analysis of MPC solution
  - Integration of the modelling and control in a virtual testbed for the MPC of DCG.
- Chapter 4 – Overview of the case study including the MPC of DCG and the technicalities of the test site; Then, the results of the application of the developed methodologies and algorithms in real-life demonstrator are presented.
- Chapter 5 – Research conclusions and directions for future work

1.8 Publications

1.8.1 Peer-reviewed journals invitation to publications

Adeleh Mohammadi, R. Sterling, J. Febres, Marcus M. Keane, "*Model Predictive Control for Efficient Operation of Cool Generation Systems",* Invited to be submitted to The Energies journal.

Adeleh Mohammadi, R. Sterling, M. Keane, "*Integration of Modelling, Simulation and Control Methodologies in District Cooling Systems"*, Invited to be submitted to the Special Issues in Energy.

1.8.2 Peer-reviewed conference publications

Adeleh Mohammadi, R. Sterling, J. Febres, Marcus M. Keane, "*Model Predictive Control for Efficient Operation of Cool Generation Systems",* Published in Proceedings of The Sustainable Energy and Environmental Protection (SEEP) conference, Nov. 2019, Sharjah, UAE.

Adeleh Mohammadi, R. Sterling, M. Keane, "*Model Predictive Control of Cool Generation Systems based on Modelica models"*, Published in Proceedings of International Building Performance Simulation Association (IBPSA) Conference, September 2019, Rome, Italy.

Raymond Sterling, Jesús Febres, Andrea Costa, **Adeleh Mohammadi**, Rafael E. Carrillo, Baptiste Schubnel, Yves Stauffer, Pietro De Cinque, Krzysztof Klobut, Marcus M. Keane, *"A virtual test-bed for building Model Predictive Control developments",* Published in Modelica conference proceeding 2019, March 2019 Germany.

Adeleh Mohammadi, R. Sterling, M. Keane, "*The Path to the Development of an Integrated Tool for District Cooling Systems Modelling, Simulation, and Control",* Published in the Proceedings of the Sustainable Energy and Environmental Protection (SEEP) conference, May 2018, UWS, UK.

1.8.3 Presentation

Adeleh Mohammadi, R. Sterling, M. Keane, "*Energy Efficient Buildings through State-of-the-art HVAC Systems Modelling and Control*", presentation in GENSIM Scientific School, October 2016, Corsica, France.

2 Literature Review

The literature in the context of modelling and control of DCS is studied with a focus on model-based approaches to efficient operation of DCS Generation. The literature is studied *critically* and *systematically* to distinguish the efficient, and applicable techniques to *model and to control the DCS* and propose the methodology for modelling, simulation technology, and control of DCS. This systematic method ensures that the results are comprehensive, replicable, and un-biased [21].

2.1 Literature Review Procedure

The following questions are posed that lead us to address the research question described in chapter 1.

- What is DCS and what are its components?
- What are the current control strategies in DCGS?
- What is model-based control?
- What is the current development and literature on the model-based control of DCGS?
- What is MPC?
- Why is MPC used to control DCGS?
- What are the difficulties and challenges of applying MPC in DCGS?
- How does the model-based control of DCGS effect the energy efficiency and optimal operation of DCGS?
- How effective are the current model-based control in real-life applications of DCGS?

The literature review map is illustrated in Figure 3.

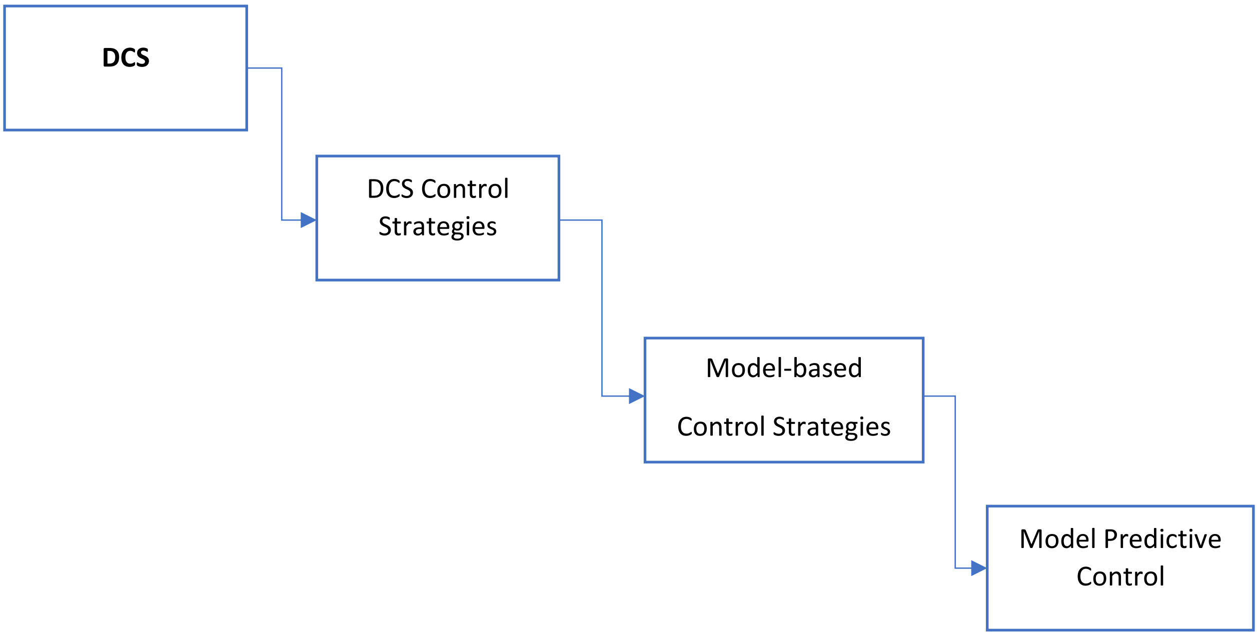


Figure 3: Literature Review Map

Figure 3 is a schematic of how the literature review is mapped. First, a comprehensive description of DCS components that compromise a working DCS is provided. The specific focus of this literature review is on the DCS control strategies and their practical implementation.

2.1.1 Filters to Find the Relevant Literature

The criteria and filters that are applied to identify the most relevant literature in the modelling and control of DCS are explained here. Based on the questions above and the introduction in Chapter 1, below is a list of related issues that make the literature relevant to the research question of this review:

- Relevant lessons from DHS in DCS; DCS versus DHS
- Energy efficiency of DCS
- Low temperature differentials in DCS
- Simulation and modelling technologies of DCS
- Control of DCS generation components
- Predictive control methods in DCS

The research strategy is to explore the main databases in the modelling and control of DCS. The flow diagram in Figure 4 is a visualization of the literature review procedure. The Databases to review include ScienceDirect, IEEE, Web-of-Science, and Scopus.

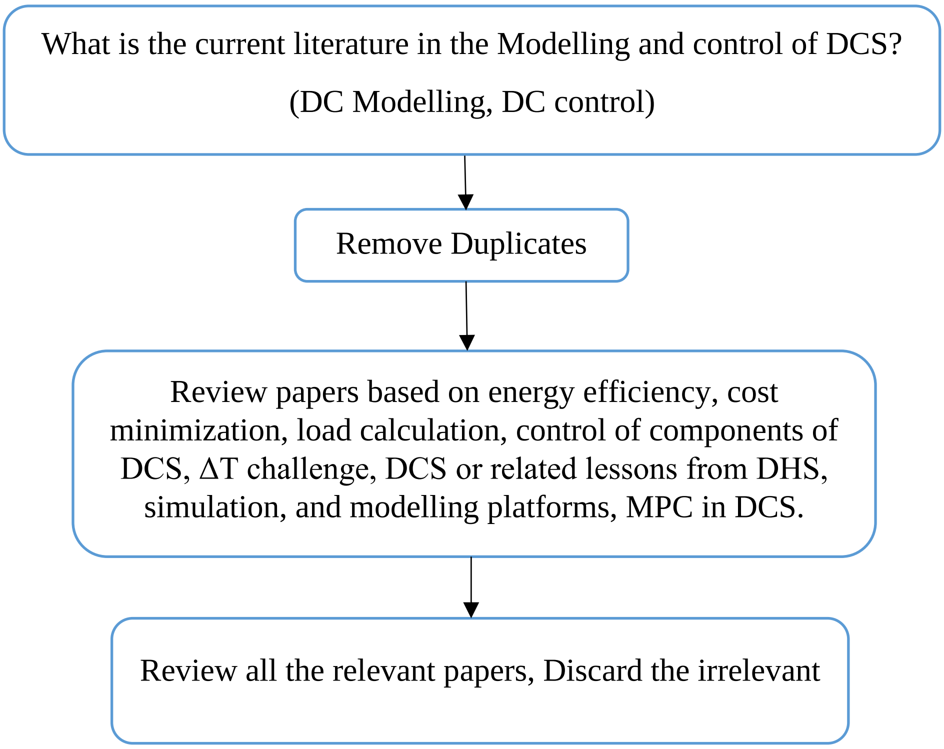


Figure 4: Flow diagram of the review procedure

To find the related literature, the keywords “District Cooling” AND “Model” OR “Modelling” have been searched in data bases ScienceDirect, IEEE, Web-of-Science, Scopus starting from 1990 to 2021. The year 1990 is particularly interesting because of two major events; first, the air-conditioning systems and energy policy management have been widely changed after the 1970s energy crisis and the oil price increased in 1990s. Second, the advancements in MPC in the industry commenced during the late 1980s. Thus, 1990 is the time of introduction of MPC in the energy industry. The references reviewed below are the most relevant literature to modelling and control of DCS after filtering the papers according to the review procedure.

2.2 Physical DCS

Understanding the physical system is essential in determining an effective control strategy for DCS. Thus, the physical components of a DCS are discussed here. The DCS is comprised of generation, distribution, and consumption sites (Figure 5).

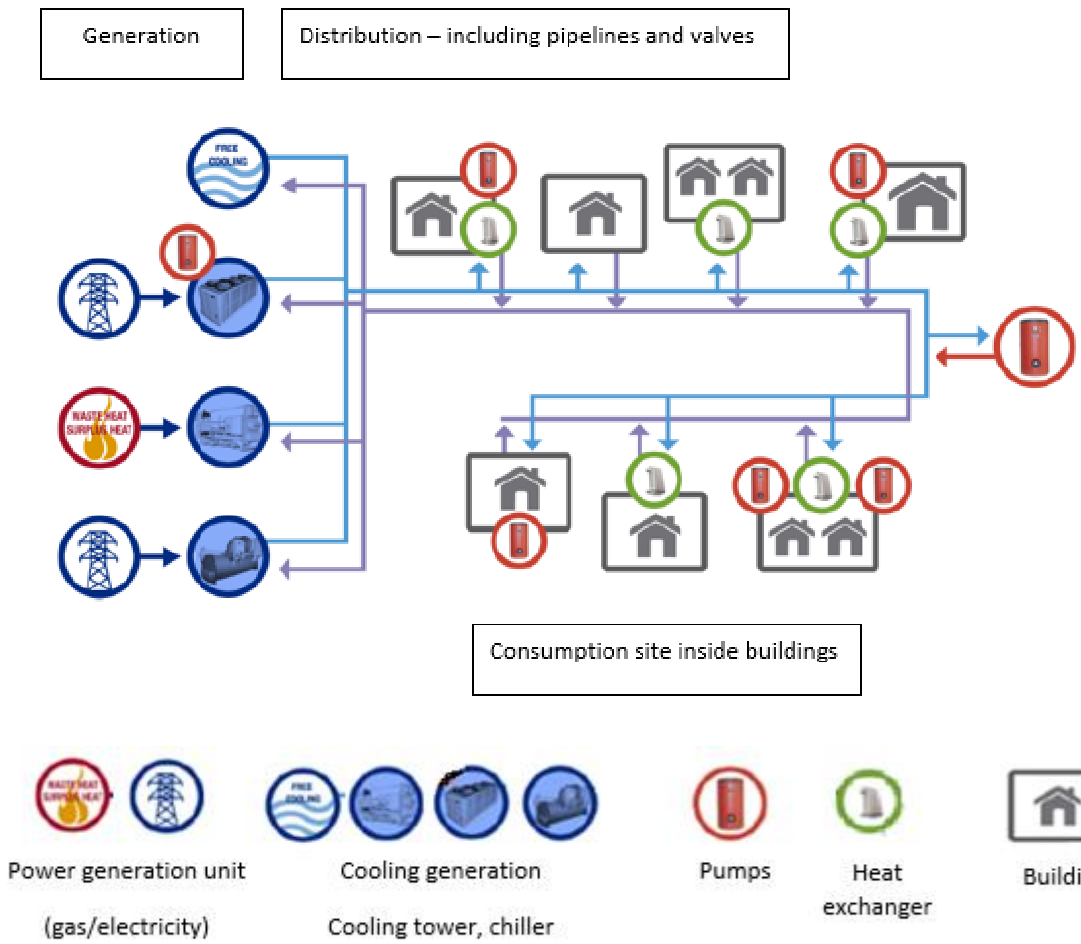


Figure 5: Engineering viewpoint of DCS (Retrieved from INDIGO project [17]*)*

The Generation is the site where chilled water is produced in chillers and the heat is rejected through heat rejection circuits and cooling towers. The chilled water is then carried to the distribution system and through the pipelines to the consumption site and end-users. The consumption site consists of the Heating, Ventilation, and Air-Conditioning (HVAC) equipment including Air Handling Units (AHU) in the buildings depicted in Figure 6.

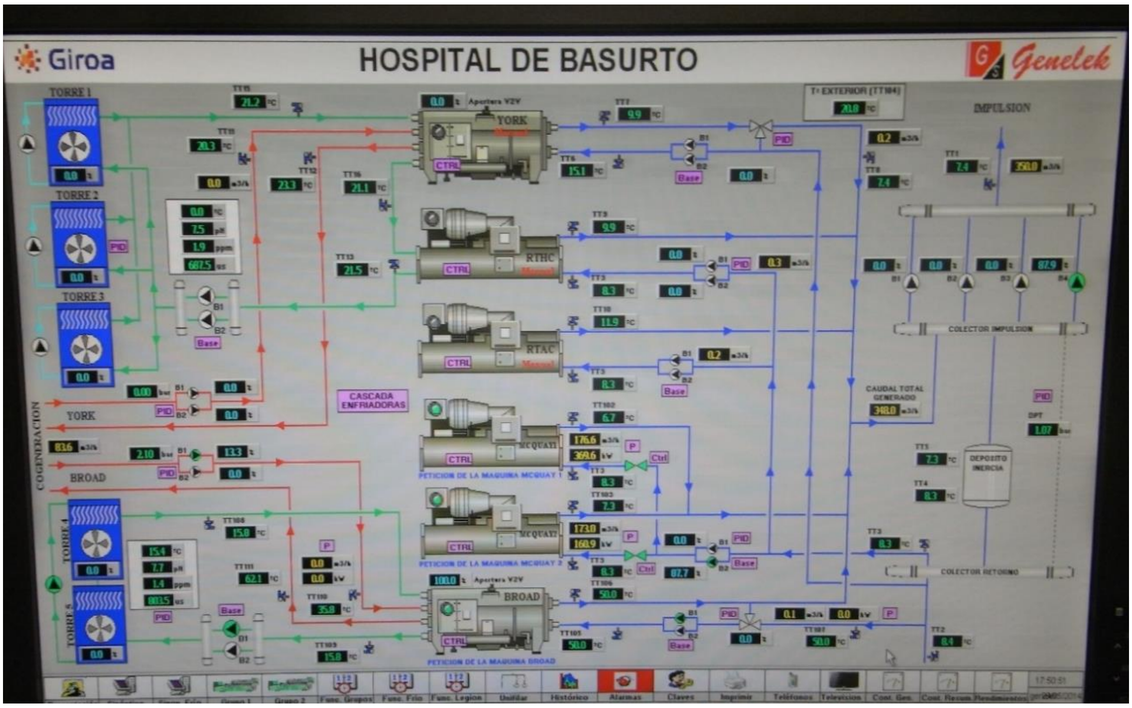


Figure 6: Schematic of DCS in Basurto hospital (Produced by Veolia in INDIGO project [17])

The heat exchangers transfer heat between the chilled water supply of DCS and the air-conditioning system of the user building and the end user equipment such as AHUs and fan coils. A summary of DCS components is provided in Table 1.

Table 1: DCS components

DCS components	Components of DCS components
Generation	Chillers
	Cooling Towers
	Storage Units
Distribution	Pumps
	Supply and return pipelines
Consumption	Air Handling Units, Fan coils
	Heat Exchangers
	Chilled water piping in the building

2.2.1 DCS Versus Individual Cooling System

Major studies have been performed to prove the effectiveness of DCS plants over individual conventional cooling plants in premises in terms of space and energy efficiency [18], [22], [23], [24], [25], [26], [27], [28]. Palm et al. [29] discussed the barriers to and the enablers of DC expansion in Sweden. The discussion shows that lack of information among the public is the main barrier to DC expansion which can be surmounted by marketing the benefits through public-private collaborations. Chan et al., [30] mentioned in their study of DC plant with ice storage that the efficiency of the overall system of DCS is higher than the individual chiller plants in buildings.

Shimoda et al., [31] defined an Energy Efficiency Ratio (EER) to compare DHC and a conventional heat source system in individual building and observed the result through a case study of 9 DHC plants and 19 individual buildings in Japan. The conclusion was that the **efficiency of the components of DHC** and the part-load operation of chillers, pumps, and fans affect the overall efficiency of the DHC. This observation strengthens the importance of our studies on the efficiency of District Cooling Generation (DCG) components efficiency. Shimoda et al. [31] approached the problem from a design optimisation perspective. However, in this thesis the existing DCS was studied to improve its efficiency by control optimisation methods [19].

2.2.2 Benefits of DCS

In practice, DCS has several advantages:

- Lowering CO_2 and greenhouse gas emissions [12]
- Lowering the maintenance and operation costs by installing centralized generation site for the whole district [32]
- Improving the balance on energy peaks and regulating demand capacity [33]
- Integrating of renewables and new technologies into DCS [32]
- Avoiding individual distributed air conditioning installations
- Reducing space requirements and providing more space on rooftops and basements

In addition, developing the DCS technology reduces the transportation costs as the combustion system is at a central location and there is no need to transport the fuel to the end users. According to [32], peak load time planning in DCS generation and storage can lead to a 27% increase in energy efficiency at the city-scale, as seen in the case of Hong Kong. Regarding the size of the district, the research in [12] pointed out that DES were beneficial to large public buildings such as commercial complexes.

2.2.3 Renewable Energy in DCS

Another way to tackle the energy efficiency of DCS is to integrate *renewable energy technology* into DCS [11], [30], [34]. Renewable energy is usually incorporated into the generation site of the district cooling. The cold-water sources in some European countries are lake, ground water, and rivers; For e.g., the DCS of Paris benefits from the cold water energy source of Seine river [35]. The researchers in Austria developed a roadmap for solar thermal cooling [36] which contributed to less carbon emission while used for DHC applications in small and large districts.

2.2.4 DCS Challenges

The literature is studied to understand the technical barriers to develop DCS. The available literature is mainly on DHS and fewer studies have been conducted on DCS compared to DHS. DHS is already well-developed and used in most parts of the world [5], [16], while DC became popular especially in the European market [14].

The main challenge in DC compared to DH is the low temperature differentials between the supply and return water. This difference is around 8°C (supply at 4°C approximately and return at 12°C approximately), while in DHS, this difference is usually greater than 40°C. The cost of pumping, the piping system, the consumption, and end-user equipment also grows because of these low differentials. Danfoss reported that "*1°C deviation lower than desired temperature will cause energy costs to increase by 10-16%; 1°C lower return temperature will result in up to 20% higher flow, increasing pumping costs with 73% and reducing chiller efficiency*" [13]. Maximization of the temperature difference is mentioned as the key to the quick growing of DCS and the energy efficiency in DCS regardless of the type of the distribution system [37].

Other challenges in DCS include the cold demand prediction compared to heat demand, the friction in the distribution pumps which results in more energy loss, and the large variation in daily cooling load. The cold demand imposes some constraints to the system such as thermal comfort boundaries and economical strategies for energy saving [38].

2.2.5 Issues with Energy Efficiency and Optimal Operation in DCS

As discussed in DCS opportunities and benefits, DCS is a solution to the increasing demand for cooling, however:

- The efficiency of the DCS generation components directly affects the overall efficiency of the DCS [31].

- Modifying the existing DCS equipment in cities and districts may be cost-prohibitive due to the built-in controls in these systems, making it impossible to upgrade them [19]. Consequently, the focus here is on improving the efficiency of existing DCS through modelling and control techniques.
- Optimisation methods in DHS are not directly applicable to DCS due to the specific challenges (mentioned above) in DCS. The main challenge is the temperature differential between supply and return water. In addition, the supply water temperature is close to freezing temperature which makes DCS more challenging.

In the following section, the modelling and control methods are categorized based on their application in DCS through the literature. Consequently, the grounds for the methodology of this thesis are set.

2.3 Control Strategies of DCS

In this section, the literature of the control of DCS is reviewed. Research has been done in the area of design and operation management of DCS [39] from a higher level. However, the focus of this section is on the control design at a *component level* rather than management, planning, or supervisory from a higher level (Figure 7). This is because the individual components of the DCS contributes to the overall optimal operation of DCS; for e.g., *chillers* are the *most energy consuming* components in DCS. In addition, the exchangeable control ideas between DHS and DCS [40] are also reviewed where the focus is on the challenges of control of DCS with existing methods.

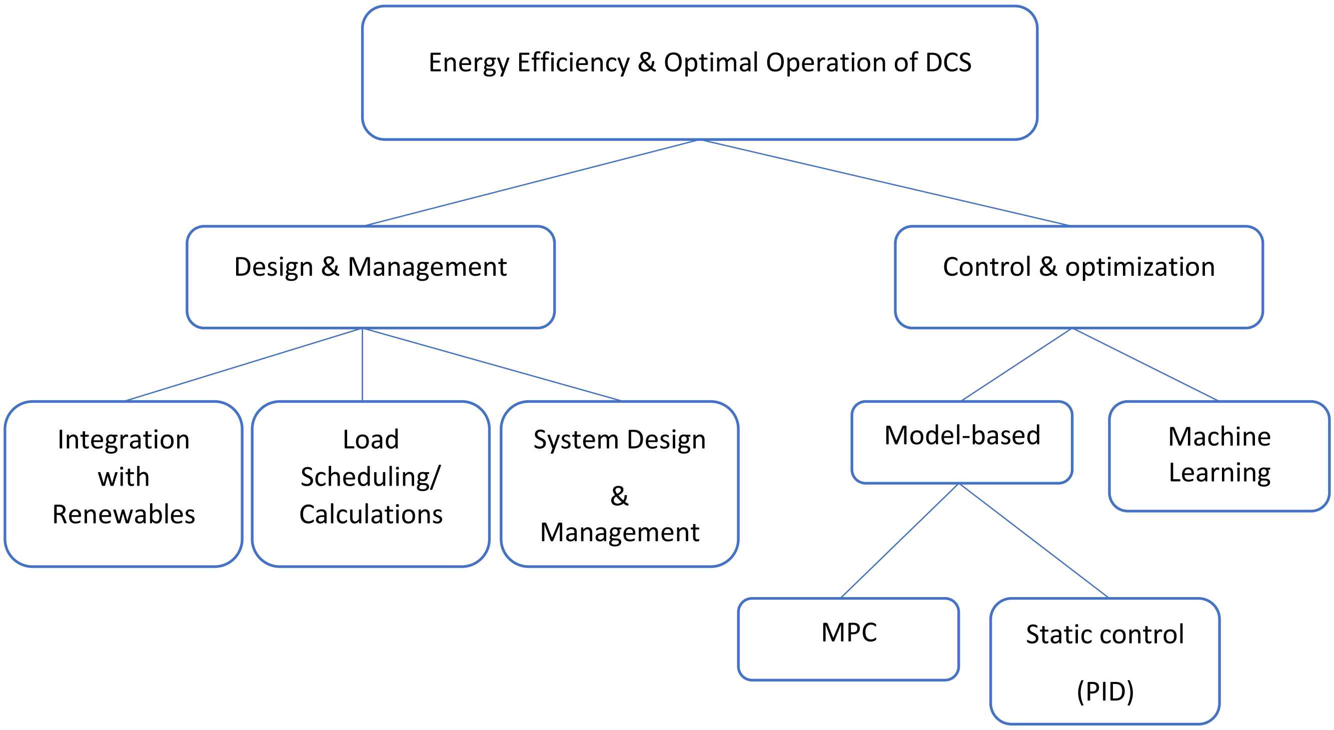


Figure 7: The existing methods in energy efficiency and optimal operation of DCS

Two general groups of control techniques are noticed in the literature: Machine Learning methods such as Fuzzy Logic, Neural Networks (NN), or Genetic Algorithms (GA) where the control method is to learn the system dynamic behaviour through one of these algorithms and control the system based on the learning process. The other class of methods are based on mathematical models derived from first principles (Figure 7). The different blocks of Figure 7 are discussed below based on the current literature.

2.3.1 Design and Management

An extensive body of literature exists on the planning and management of various components of DCS. Jing et al., provided a comprehensive dynamic model of a small-scale DHCS based on their *physical models and operations* [41]. This paper can be used as a basis to solve the modelling problem of DCS in a large scale. The models were simplified to describe heat exchanges in Linear Equation dynamics. However, the simplifying assumptions that all the buildings have the same heating capacity takes away the challenge of *district* cooling. Practical aspects of modelling and control of HVAC systems have been thoroughly considered in [42] where the importance of models has been noticed in the control process. It is mentioned that careful modelling of the HVAC system promises a more straightforward control and fault detection; furthermore, a low-performance controller usually reveals an issue in the modelling. The purpose of [43] is to schedule the operations of DHC to minimize the costs based on component operation optimisation; this is done through providing optimisation models of the storage and consumption components. In [30] simulations are performed to test the energy use of the plant in different ice-storage scenarios. Gao et al. in [39] studied the energy performance and the impact of DCS in a DES on the grid in subtropical weather. One characteristic of DCS is that it has multiple buildings as users. If taking each building as an agent, multi-agent concept can be implemented in the DCS to improve the operation of the DCS from a global viewpoint. Looking at DCS as a multi-agent system has been studied in the building energy system in [44]–[46].

2.3.1.1 Demand Side and Load Prediction

Another area that has been studied in DCS literature is the load calculation and *demand management* in DCS. The load scheduling using GA and optimisation techniques [47], hourly load prediction [48], predictions of the cooling load using NN [33], and building design load computation [23] have been used in cost minimization and efficient distribution of chilled water through the district. Khir et al. [49] minimized the operation costs of DCS by scheduling the operation time of the different components of DCS and solving a linear constraint problem based on the demand. In addition, DCS with ice-storage systems based on load-levelling methods could save around 4% of the annual operation costs, which were recommended in the design of DCS in [32]. These methods looked at DCS from a high-level point-of-view to schedule the load and model the energy use of buildings. However, in this research the aim is to **model the DCS from a dynamic system and component-level point-of-view** because *chillers* are the *most energy consuming* components in DCS.

The review of the DCS in the introduction of [49] also confirmed the lack of literature in optimizing the operation of DCS. Since *chillers* are the *most energy consuming* components in DCS, the variables of the chilled water generation system were studied. The generation system variables are the supply water temperature and flow rate, the return water temperature, and the supply and return water temperature differentials. Zhang et al. [50] considered the DCS temperature differentials and focused on the economic benefits of optimizing the temperature differentials based on the time of the year. The temperature of the return water and its effects on the DCS output have been studied in [51]. In [52], the authors introduced a method to deliver constant flow rate temperature difference in the DC Network based on the cooling load calculations. The result was that the efficiency of the chilled water distribution can be improved by adjusting the temperature difference flow rate in the central cooling network. The results presented in [52] reveal a proportional relationship between temperature difference and cooling load under a constant supply water flow rate.

2.3.2 Control and Optimisation

The static control approach calculates the control signal based on a fixed objective function that is not updated at every instant. Therefore, these methods are not suitable for systems with significant changes in dynamic and physical constraints. Since the objective function of static control remains fixed even as the system dynamics change, it does not reflect changes in the system dynamics in the optimisation problem. Model Predictive Control (MPC) is a technique that takes advantage of mathematical models and considers constraints at every sampling. In this way, changes in system dynamics are reflected in the objective function at every current simulation period. The following subsections provide further details on these methods through the literature [53].

2.3.3 Machine Learning Methods

Skawa et al. [54] formulated the operation of DHCS as a linear programming problem and solved this problem using a GA method. A self-tuning PID control is considered to adjust the temperature of supply water in DCS generation [55]. The chillers and cooling towers in the generation site of a DCS consume a considerable amount of energy to produce chilled water for the district [56], [57]. May et al. [58] use Fuzzy Logic to control the energy efficient performance of chiller systems; however, this paper is based on the fundamental evolution of control methods, such as fuzzy control, at that time. The authors do not provide any dynamic equation for the chillers and control variables. This means the chillers are considered as components with constant dynamics which does not reflect the actual physical system of a chiller which is dynamic.

There are several reasons for using Machine Learning approaches in DCS operation:

- There is one or more optimisation problems to solve.
- There is access to large amount of data from the physical system.
- There are too many variables involved in the modelling of the physical system and it is difficult to find explicit equations which relate the variables to each other. This makes the modelling cumbersome.

NN has been used for optimal control of DCS in [59]. The authors use a NN as the DCS plant under study is complicated; In addition, they have continuous measured data from the plant.

2.4 Model-based Control of DCS

The emergence of state-space models by Kalman in 1960 and the wide-spread use of optimal control techniques in 1970s gave rise to model-based control strategies. Model-based control strategies such as robust, optimal and predictive control require identifying a model for the plant and then designing the control based on that model [60].

Predictive control strategies such as MPC rely on dynamic models of the system to be controlled. These models are used to predict the response of the system to a control signal inside the optimisation algorithm. As a result, the role of modelling with respect to DCS control needs to be further investigated.

2.4.1 Role of Modelling with Respect to DCS Control

Models represent the dynamic behaviour of the system. In practice, the model is at the heart of the operation of a system because the physics of the system can be brought into simulation through a model. Figure 8 is a graphical relationship of the modelling and control in Dynamic System Theory.

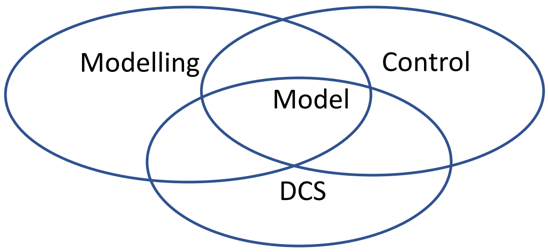


Figure 8: Relationship between modelling and control in DCS

In this study, the dynamic model refers to the model that is represented by mathematical equations that relate the variables and parameters of the system to each other.

To study the energy efficiency and performance of DCS using model-based control strategies, the practice of DCS modelling in the current literature is identified (Figure 9).

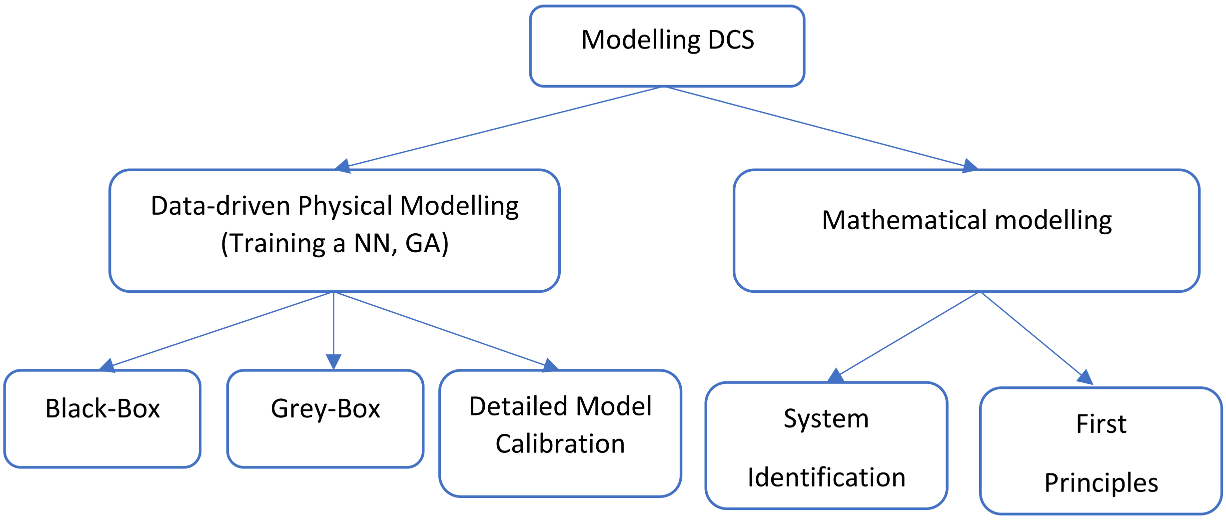


Figure 9: Modelling methods for DCS

Modelling based on the physical characteristics of the system and measured input/output data was performed to adjust the parameters or system configuration in a way that it best represents the data. For example, Bacher et al. [61] identified models for the heat dynamics of buildings. These models were based on both the **physical knowledge of the system and the measurement data** [62]. The complexity of the model could also be tuned based on the statistical significance of the parameters. In addition, an interpretation of the model and its uncertainties was presented using the *Maximum Likelihood Estimation*. However, the evaluation of these models still highly relied on the modeler's judgment in choice of the **minimum accepted error, degree of the complexity of the model, and trial and error**. These methods are not suitable for all DCS systems because they require specifications for every single system and case-to-case system configuration.

On the other hand, **first principles** are the basis to create the models for DCS. In [63] and [64], energy balance equations were used to derive the dynamic equations of the air-to-air plate heat exchanger, and water-to-air coil without condensation. Using the first principles to model the components of HVAC systems is valuable for design purposes; However, to control these heat exchangers, a simplified dynamic model is needed [65].

According to [65], modelling of HVAC equipment was performed to provide either a *Reference Model* to consider the physical system and mathematical derivations in continuous time or a *Lumped Model* with simplifications such as discretization of time and space and dynamic models in the form of Ordinary Differential Equations (ODE); the latter is of our interest in this thesis. The mathematical modelling approach using the first principles can include the constraints and physical limitations of the system in the models.

Tashtoush et al. [66] modelled the HVAC system of a zone in a building using energy balance equations and thermodynamic laws. However, many simplifications have been made, which reduces the reliability of the model and therefore the basis of control. Despite all these simplifying assumptions, no uncertainty quantification has been studied. To validate the model, the authors studied the Step Response (output of the system in response to a step signal) and the transient behaviour of the system which does not include all system dynamics due to the poor excitation of the step signal. As a result, the derived model lacks the significant frequencies of the system. However, this model can still be used to initialize the simulation in model-based controllers.

The distribution pipelines, the insulation thickness, and the cold energy wasted by the friction between the chilled-water and the pipes have been discussed in [67], [68], [69]. In addition, an optimal design of the DCS piping network using genetic algorithm was proposed in [70]. In an attempt to optimize the supply cold-water, the optimal choice of supply equipment in a DHC using dynamic programming approach was discussed in [71]. These papers focused on the optimal operation of the distribution and piping network of the DCS using Machine Learning methods.

A review of modelling methods of DHS have been discussed in [72]. Then, the thermo-hydraulic models of DH were presented by Ordinary Differential Equations (ODE) and simulated in Modelica. The paper suggested a modelling and simulation approach that needs to be adapted to DCS to be practical. The models in all the above researches were validated based on either real data measurements or through a Virtual Data Model [60]. These models are approximations of the actual system, so the errors are unavoidable. These validated models then facilitate the control algorithm; thus, the control results need to be validated against the errors in the modelling process too. The physical chillers and cooling towers in the DCS generation should also obey this process.

A summary of the modelling approaches for DCS as well as the modelling platform and tools used in each article of the reviewed literature are provided in Table 2.

Table 2: Modelling approaches for DCS operation

Reference	Modelling Platform	Remarks
[35]	Modelica	Validated Modelica models of DCS of East-Paris
[61]	MATLAB	Stochastic models
[66]	MATLAB	Energy balance equations and thermodynamic laws
[63], [64]	Modelica	Energy balance equations for air-to-air plate heat exchanger and water-to-air coil
[47]	DOE-2 building energy simulation software	Genetic algorithm DCS load scheduling
[49]	Optimisation software package ILOG CPLEX	Optimize the operation time of DCS components, Mixed integer programming
[72]	Modelica	ODE models and thermo-hydraulic simulation of DH

According to Table 2, the most widely used technology in modelling DCS for control are Modelica and MATLAB. Both these technologies take advantage of the dynamic model of the system which is based on mathematical equations.

2.5 Technology Framework

Various tools exist to simulate the energy systems and buildings operations depending on the purpose of the developer, such as EnergyPlus [73], TRNSYS [74], MATLAB and Modelica [75].

According to the review in [19] of model-based techniques, TRNSYS and EnergyPlus are energy system simulation tools. EnergyPlus is a whole building energy simulation software, whose development is funded by the U.S. Department of Energy – Building Technologies Office. It is free, open-source, and cross-platform. In EnergyPlus, many physical-mathematical models relative to the building physics (as well as to the HVAC systems) are already available and validated. The input data are inserted in EnergyPlus through “objects” that can be considered as vectors containing information, divided in alpha and numeric fields. The input information can be relative to the control for the simulation (e.g. calculation time steps), or to physical phenomena (e.g. air infiltration), or to elements (e.g. a wall). EnergyPlus is useful for modelling the details of the different energy/HVAC systems in a building and evaluating the building performance in long periods of simulations.

TRNSYS is a system simulation program with a modular structure which implements a component-based simulation approach. TRNSYS can be used for building energy simulations. Furthermore, TRNSYS requires long simulation times because of employing a fixed time step length. Another important point to consider is that the initial state values need to be updated in every optimisation of the MPC problem. This feature is not available in these tools without updating the code [19].

The data exchange and the integration of models of dynamic systems have been performed through Functional Mock-up Interfaces (FMI) standards [76] through the literature. FMI is a tool to standardise data exchange and model integration among simulation software packages. The authors provide a comprehensive technology framework to model and simulate the energy systems and buildings based on equation-based and open source modelling language of Modelica in [77]. The authors explain the recent developments in the *Buildings* library of Modelica. *Buildings* is a library in Modelica with a focus on modelling thermal zones, air-flow, heat transfers (conduction, convection, radiation) in a zone, HVAC systems, and thermal comfort factors in a building in [78].

Wetter et al. [78] focus on modelling and simulation of a room, the boundaries of a thermal zone, and the extension to model the electricity distribution system. These extensions are very important as this allows the developer to have a complete model of the building with all its components ranging from electrical distribution system to HVAC and thermal boundaries. In addition, the extensions are intended to model the building for HVAC control purposes which makes it very useful in our study. The *Buildings* library in Modelica has been motivated by the need to have an integrated library which could simulate the various systems in a building and provide a comprehensive model of all the equipment and units in a building.

One benefit of Modelica which makes it easy and accessible to use is that it is open-source, freely available and non-proprietary. Developers from around the world have contributed their own libraries to extend and enhance Modelica, further transforming it into a user-friendly simulation and modelling language. Modelica library developers have written various libraries on building and thermodynamic systems modelling which can be used to model the HVAC systems of a building; examples are heat transfer and solid materials thermal modelling library, building Systems library, Buildings, IEA and IBPSA-1 Annex 60 library for simulation of building and community energy systems [77]. This is all because Modelica designed to support effective library development and model exchange among various environments. A summary of the technology framework for simulation and implementation of DCS is in Table 3.

Table 3: Buildings and energy systems technology framework

Modelling Software	Main features
Ansys	Design analysis and modelling, advanced computation tools
EnergyPlus	Energy load simulation, well linked to other simulation environments, simulation of the lighting/heating/weather data related to the buildings
MATLAB and SIMULINK	Dynamic system analysis and control tools, computation, and optimisation tools available
Modelica	Explicit simulation of complex dynamical equations, component-based graphical interface for system simulation, ability to integrate the models with control systems.

According to Table 3, the key strength of Modelica is that it simulates dynamical equations without prior mathematical manipulation into an *explicit equation* and no variable is required to be solved for manually (as opposed to other simulation environments like MATLAB). This decreases the manual errors in the calculations and avoids cumbersome manipulations to derive explicit equations of variables.

2.5.1 Model Validation and Calibration

Following the simulation of the dynamic model of DCS in the appropriate simulation program, the model parameters need to be calibrated based on the physical data and validate the performance of the model through simulations.

Werner [14] described the lack of validated and trustworthy data on European cooling systems and demand, and as a remedy, provided data on recent cooling demands in Europe based on the aggregated data from different countries. This information about the demand site can be used in strategic management and planning of DCS and validation and calibration of the models.

Gang et al. [24] proposed a design methodology for DCS that considered uncertainty in the DCS variables such as load, weather data, and demand. The method then considered an optimised design of the DCS. The results are of the case study in Hong Kong show that DCS can be modelled in size and configuration against the uncertainty analysis. Damien et al. [35]

presented the Modelica simulations and model validation of the cooling system of a region in Paris. The paper was a case study of the application of Modelica in modelling DCS and the validation of the identified model using real data. These results can be beneficial in evaluating our future case study; However, the authors did not discuss the control techniques of DCS. In [79] the central chilling system of a building in Hong Kong has been mathematically modelled and validated in terms of dynamic equations and software simulations which backs up a mathematical approach to DCS simulations.

Coakley et al. [80] provided comprehensive reviews on the recent calibration methods in building simulations and modelling. The calibration methods have been classified into "manual" and "automated" methods, where manual represent the iterative, trial-and-error methods while automated involves statistical analysis. The uncertainty arising from the mismatch between model and physical plant is also mentioned. It was noted that due to the presence of uncertainty in the system, the model cannot fully represent the reality. Although, the authors of [80] looked at the problem from a general point of view of building simulation rather than detailing the challenges of DCS. The focus of their work was mainly on the calibration methodology to build more accurate models representing reality, while the emphasis in this thesis is on how this accuracy can be beneficial for control purposes in DCS.

2.5.2 Model Predictive Control

The purpose of controlling the DCS is to satisfy the desired conditions in the environment by setting the amount of cooling [42]. These methods range from conventional control techniques such as PID control [66] to recent advancements in MPC in the industry [81]. MPC has been used in control of DCS systems as a replacement for former control methods like PIDs or on-and-off controllers since it allows to introduce the constraints of the system and optimises the solution subject to constraints with desired objective.

Ma et al. [6] formulated an MPC problem to minimize the energy use and to maximize the Coefficient of Performance (COP) of an office building based on the predictions of the thermal load model. First, they provided and validated the models of chillers, storage tanks, fan coils, and the building load model; then designed a model predictive controller which considered the constraints of the system. The objective of the control problem was to *minimize the electricity bills and maximize the plant efficiency*. The load has been overpredicted because of the parameters chosen for the model. In addition, the model of the chillers and cooling towers have not been incorporated in the MPC formulation and predictions. Later in [82] they improved the results by incorporating the chillers and cooling towers models and introducing a terminal constraint for the stability analysis of the MPC solutions. However, the models are still at a very simple stage while proved to work in the application of the algorithm in the office building of the case study.

In [83], the state estimation and MPC of a building zone air-conditioning system has been studied. The building zone was modelled in Modelica using a famous *Resistance-Capacitance (RC)* model of a zone in the building [84]. This model was then used as an *emulator* which is validated using the measurements data from the building. A Moving Horizon Estimation (MHE) approach was applied for state estimation and the measurement data is adapted to the RC model. The validated model served as the basis for model-based control. The objective of the modelling and control was to achieve more efficient buildings, with lower energy use and costs, and a higher level of thermal comfort. These factors have been incorporated into the objective function of the MPC problem.

A summary of the control methodologies for DCS is provided in Table 4.

Table 4: DCS Control Methods in the literature

Reference	Control Method	Remarks
[66]	**PID**	Dynamic modelling of HVAC system for control, PID control to reduce energy use, Ziegler-Nichol's rule to tune PID
[55]	**Self-tuning PID**	PID to adjust the temperature of supply water
[43]	**Linear programming**	Minimize the operating cost of the plants, handle thermal storage tanks
[6]	**MPC**	Simplified models of HVAC components, real-time implementation of MPC, validated control strategy, reduction of electricity cost, efficiency improvement of power generation plant
[54]	**GA, Linear programming**	Operation planning, scheduling of demand, cooling, and heating demand response analysis
[58]	**Fuzzy control**	Operation of a chiller system controlled by fuzzy logic and compared to conventional Programmable Logic Controllers (PLC)

[82]	**Robust MPC**	Design and analysis of MPC on a real-life application of DCS generation
[83]	**MPC, MHE**	State estimation, use of real-time data to validate the MPC controller

Table 4 shows that most of the research in DCS control have taken advantage of the model-based control strategies that facilitates the control of DCS based on validated mathematical models. However, most of these control techniques are still at the simple stages of using PID or optimal control rather than predictive control. In the next section, the generation component literature is investigated to find the recent advances in predictive control in DCG.

2.6 Generation Component

The components in the generation are chillers, cooling towers, and storage units. *Chillers* are the *most energy consuming* components in DCS. Chillers and cooling towers together in a loop generate chilled water (Figure 10).

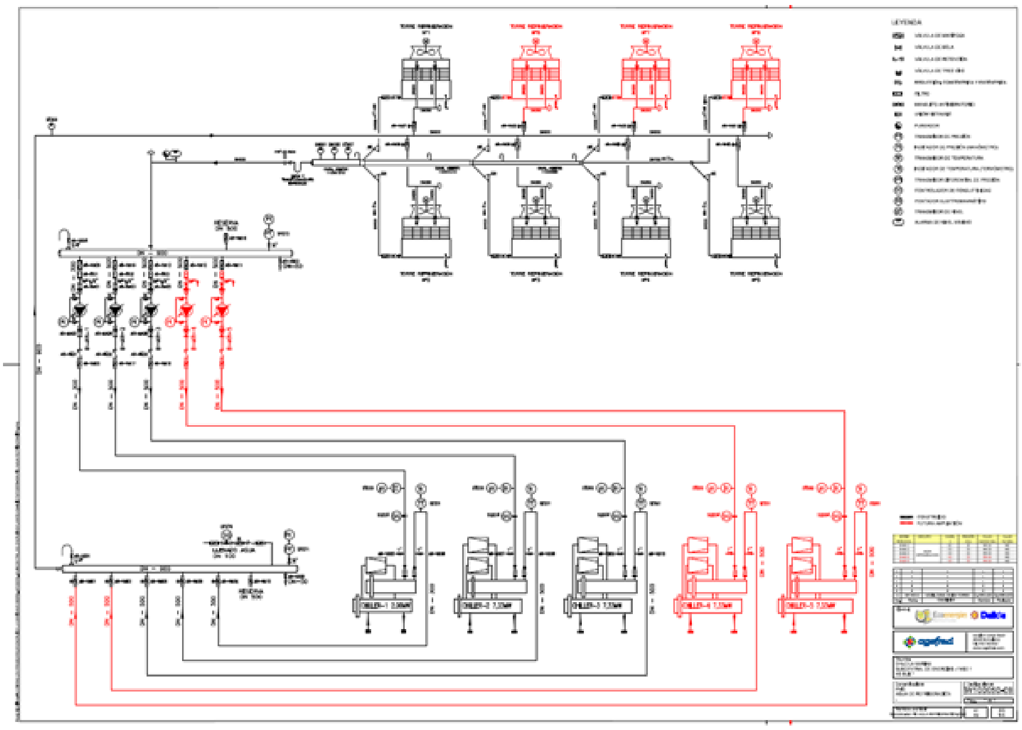


Figure 10: Schematic of chillers and cooling towers in LaMarina of INDIGO project (Retrieved from INDIGO project [17])

The chillers (Figure 11) remove the heat from water in inner chiller loop which can be absorption [85], [86] or vapor-compression [87]. The heat is then rejected through the heat rejection circuit between the chiller and cooling tower to the ambient. A fan at the outer circle of the cooling tower is responsible for heat rejection to the environment.

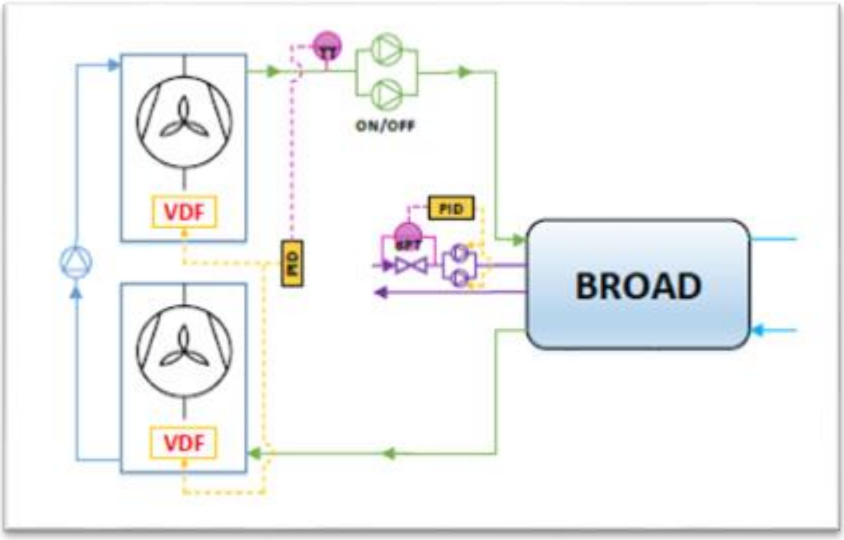


Figure 11: BROAD chiller in Basurto Hospital of INDIGO project (Retrieved from INDIGO project [17]*)*

The generation components in the case study of this thesis are not currently operating in optimal mode because the modelling and technology framework to control these components are at a simple stage. In addition, chillers and pumps are generally controlled via classical control methods, with some planning or sequencing strategies applied in an ad-hoc or non-automated manner [88]. More novel methodologies have rarely been extended to general industrial applications.

2.6.1 Physical control parameters of DC Generation

The chiller and the cooling tower are working together in a heat rejection circuit. The chilled water from the cooling tower flows through the condenser in the chiller with a given temperature and flow rate. For each generation site, an assessment of the plant's sub-systems has been carried out. The entire Generation plant must be *decoupled into sub-systems*, and the main sub-systems need to be identified. This results in a set of groups of components. The main criteria for defining the component groups are the independency of operation. It means that components that interoperate between each other must be part of the same group. For instance, if a cooling tower is serving two chillers, the components (cooling tower and two chillers) would be in the same group. In this way, an MPC is developed for each component group. The physical control parameters are supply and return temperature and supply flow rate in the chiller. The idea is to optimize the group operation by modifying each component's setpoints.

2.6.2 DC Generation control literature

The chillers and cooling towers in the generation site of a DCS consume a considerable amount of energy to produce chilled water for the district [57]. Thus, chillers are one important part of the *objective function* in operation optimisation of DCS. The power use of the fan is usually another objective function term to be considered in generation operation efficiency.

Since our purpose is optimal operation and efficiency of DCS, for the above reason, we need to study the current approaches that are taken for optimal operation of generation component. In this section, the same approach for systematic literature review of DCS is taken for its generation component. The latest methods of MPC in controlling chillers and cooling towers are reviewed (Figure 12).

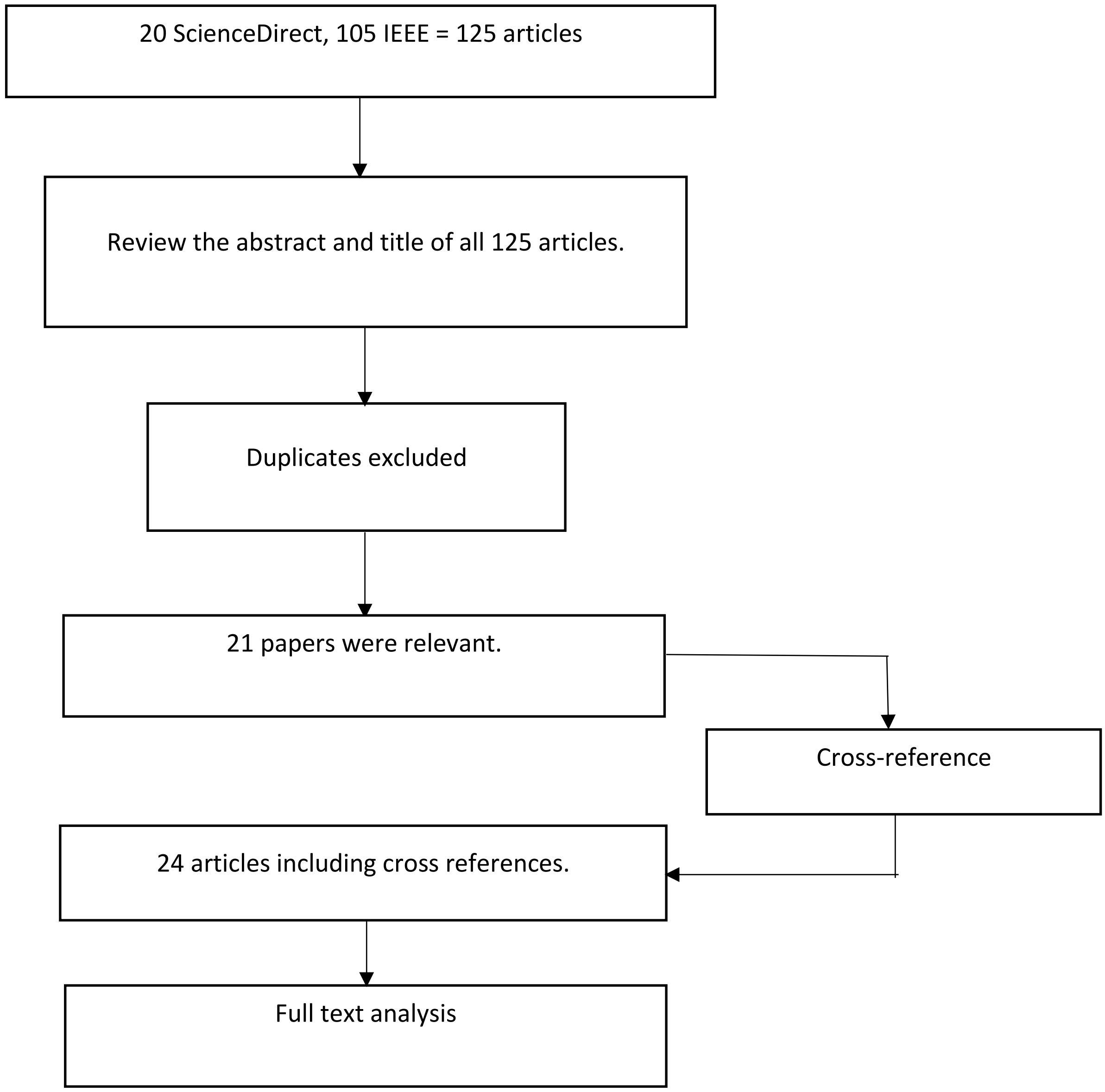


Figure 12: Systematic Literature Review of MPC of chillers and cooling towers

Systematic Literature Review of “Model Predictive Control” AND [“chiller” OR “Cooling tower”] keywords

Some research have been conducted to control the generation of chilled water in efficient ways [58], [89]–[91]. The central chilling system of a building in Hong Kong has been mathematically modelled and validated in terms of dynamic equations and software simulations [79].

Ma et al. [6] formulated an MPC problem to minimize the energy use and to maximize the COP of an office building based on the predictions of the thermal load model. The load has been overpredicted because of the parameters chosen for the model. In addition, the model of the chillers and cooling towers have not been incorporated in the MPC formulation and predictions. Later, Ma et al. [82] modelled and designed a chilled water storage and then implement a predictive controller for the simple model. First, they provided and validated the models of chillers, storage tanks, fan coils, and the building load model; then designed a model predictive controller which considers the constraints of the system. The objective of the control problem was to minimize the electricity bills and maximize the plant efficiency. The focus of [82] is on the modelling and control of the generation and distribution sites which is mainly storage units and tanks.

Schalbart et al. [92] used predictive control for the energy efficient operation of food storage. The optimal operation of DCG was discussed in [93]. Bau et al. [94] designed a linear gradient-based optimisation problem for optimal control of an absorption chiller. The authors verified the results by a case study of a solar cooling absorption chiller. Antonov et al. [95] presented a robust MPC strategy for absorption chillers and increased the produced cooling energy by 21.6%. The focus of [95] was on system robustness to state estimation uncertainty. Lara et al. [96] integrated the building simulation tool with real data of a hotel building and proposed a model for the cooling dynamics of a central chiller plant.

Feng et al. [97] implemented an MPC for a radiant slab cooling system and presented a case study to compare MPC with rule-based control methods. Deng et al. [98] considered the On/Off scheduling problem of a central chiller plant by formulating an MPC and mixed integer programming problem; The result was reduced electricity use costs. They later expanded the results in [91] and established a bilinear model to schedule the chillers operation and satisfy the cooling demands of a university campus case study.

Yan et al. [99] investigated the energy efficiency of chiller operation by genetic algorithm optimisation. Kane et al. [44] focus on the design parameters of the MPC and analyse the form of the objective function and structure of the model used for optimisation.

The current practice in the field of energy efficiency of DCG is summarized in Table 5.

Table 5: Literature review of DCG modelling and control

Reference	**Methodology**	**Impact**
[79]	Mathematical modelling of central chilling system	Application of DCS in subtropical weather
[6], [100]	Prediction of thermal load model using MPC	MPC to maximize efficiency and minimize cost
[94]	Gradient-based optimisation	Optimal control of absorption chiller
[95]	State estimation and robust performance	Uncertainty evaluation
[96]	Data-driven modelling of chiller	Modelling the cooling dynamic including a case study
[97]	MPC implementation for a case study	Comparison of MPC and static control
[98]	ON/OFF scheduling of central chilling system	Reducing energy costs using MPC

According to Table 5, there is a gap in the literature regarding the integration of simulation tools studied in the last section with the optimal operation of chillers. In addition, the models are at a simple stage. MPC is a newly exploited technology in the control and operation of DCG, and the gap exists in an integrated framework for modelling and control of DCG.

2.6.3 Theoretical Solution to DCG Control

The reviewed literature generally provides a case study of district cooling components to prove the methodology under study; However, in this thesis, the study is on the cool generation system from a mathematical point of view to provide not only the case study but a firm and concrete mathematical derivation for the optimal solution of chiller energy use. The idea has been noticed in theoretical works in other fields such as MPC for engine control [101], or

building energy storage units [102]. Ma et al. introduce a moving or receding horizon control strategy in [103] which used *Gradient* methods [104] to solve the optimisation problem.
In the theoretical framework, the goal is to solve the MPC optimisation problem using optimisation theory and generate theorems for MPC optimality and performance which can be applied to similar MPC problems in other building components.

2.7 Literature Review Conclusions

This review was conducted systematically with a focus on identifying gaps in the modelling and control methodologies of DCS. Here are some key findings of this review:

- DCS can be 5 to 10 times more energy efficient than individual distributed cooling systems. However, the effectiveness of DCS depends on the modelling and control methodologies that are used for its optimal operation and energy efficiency. Gang et al. [105] performed a review of DCS including the history of DCS, optimisation, planning, and integration of DCS with renewable energies. The future work of the review article [105] suggests that there is a gap in the *optimal performance of DCS and the integration of DCS with new technologies*. This was a key result that leads this research thesis.
- DCS has been mentioned as one of the pillars of energy efficiency goals in the EU energy efficiency directives [4]. DCS has proved to be more energy efficient than distributed cooling system in different case studies in the literature [105] because distributed cooling requires individual cool water generation and storage for every section of the district. In addition, DCS has come into consideration for reducing CO_2 emission. This thesis includes CO_2 emission reduction implicitly by reducing the energy use as well as choosing an optimal set-point for the thermal comfort.

- The work on Distributed Energy Systems (DES) needs to be expanded with a focus on DCS because of DCS specific challenges: Low temperature differences (ΔT) between the supply and return water and the large energy use in components like chillers [106]. These challenges make many developed methods in DH inapplicable in DC.

- A systematic review is developed focusing on modelling technology framework and model-based control techniques in DCS and specifically DCG. This review is beneficial to expand the work in [82] regarding *modelling the components of DCS and developing advanced MPC theory* for DES. This systematic Literature review ensures that the outcomes are un-biased and replicable.

- DCS is composed of generation, distribution, and consumption components. Chillers in generation consume a large percentage of energy in DCS. Most of the studies examine the chiller as an individual component rather than in a district generation component.

- A review of the modelling and simulation technology framework of DCS confirms that the Modelica language is an appropriate tool to simulate the DCS models [107]. Modelica is an *object-oriented, open-source, equation-based* language to model dynamical systems. It has become one of the key tools used in modelling and simulation of energy systems and buildings for energy analysis, thermal load calculation, and control design.

- Several studies have been performed on design and management of DCS to optimize its operation by scheduling the load, however, the efficient control algorithms of DCS have been less-studied. So, the control of chillers in DCS needs further study.

- A gap exists in applying MPC in practice and real-life applications of DCS. Although MPC is a developed technology among control theory researchers, there is still a gap in applying MPC theories in energy systems like DCG. MPC can be exploited to control the different components of DCS as well as its overall management. In this thesis, MPC is applied to the components of generation as chillers are the most energy consuming components of DCS. The overall management of DCS is studied further within the EU H2020 INDIGO (2016-2020) project [17].

- The work in the field of control of DCG also exploit the machine learning or static control approaches. However, advanced MPC technologies have only been applied in the work of Ma et al. [103] by using a predictive knowledge of weather and occupancy to regulate the building temperatures.

- There is lack of a concrete mathematical analysis of the MPC solution of DCG. The mathematical analysis sheds lights on the optimality and performance of the MPC and strengthens the reasons for using MPC on the real-life applications of DCG [104].

- The proposed approach in this thesis integrates the tools to model and control the DCG. While current modelling tools are useful for simulating the physical behaviour of DCS, they do not take into account the implementation of control strategies for optimizing performance. As a result, more advanced modelling tools are needed that can integrate both the physical and control aspects of DCS for effective MPC. FMIs combine the different software and platforms in dynamic simulation and in implementation and provide data exchange among them.

- Many reviewed articles focused on either modelling or design optimisation of DCS. There is a lack of connection between the modelling and control of DCS: How the details and methods of modelling affect the control performance and energy efficiency of the overall system?

This study aims to contribute to the integration of the latest control technologies, such as predictive control, and Modelica simulations into DCS, as identified in previous literature [81] , [108]. As these model-based controllers rely on the dynamic model of the system, this thesis aims at reviewing the current technologies in modelling and then developing an integrated modelling and control path for energy efficient and optimal operation of DCS (summary in Table 6).

Table 6: Literature Review conclusion and proposed methodology

Main result	Current state	After this thesis
DCS optimisation and planning	Gap identified in the optimal performance of DCS and the integration of DCS with new technologies.	DCS optimisation with novel predictive control and mathematical justification
Model-based approach to DCS	Application of the technology for DCS is still at research level with reduced size test cases being reported in the scientific literature.	The mathematical modelling approach can include the constraints and physical limitations of the system in the models.
Predictive Controllers implementation for DCG in real-life	Predictive controllers have been widely used in different applications, even in some DC components (e.g., generators). However, chillers and pumps are generally controlled via classical control methods, with some planning or sequencing strategies applied in an ad hoc or non-automated manner. More	Predictive control is designed and applied to real-life case of DCG.

	novel methodologies have rarely been extended to general industrial applications.	
Technology Framework	The current modelling tools are not appropriate for MPC because they are only made for modelling the physical system but not the control process implementation. The use of Modelica in modelling DCS is at a very early stage.	Use of Modelica and MATLAB as the technology framework for modelling and control of DCG.
Mathematical Analysis of MPC solution	Lack of a concrete mathematical analysis of the MPC solution.	The mathematical analysis casts clarity on the optimality and performance of the MPC and strengthens the reasons for using MPC on the real-life applications of DCG.

3 Chapter 3: Methodology

3.1 Introduction

This chapter is dedicated to explaining the methodology of optimal operation of DCS. To deliver high efficiency, DCS needs the support of the modelling and simulation in buildings which should improve their operations and energy use to the maximum. Consequently, in this research the aim is to improve the energy efficiency and optimizing energy use in DCGS which is the most energy consuming component of DCS. More efficient, intelligent, and economical cohort of DCG based on the real-life implementation of optimal and model predictive control is developed. As predictive controllers rely on the dynamic model of the system for predictions, models that consider the main characteristics and the inherent uncertainties of the system for a more reliable control performance are presented.

Based on the literature review conclusions, the methodology consists of the following sections:

- Overall Engineering of the DCG (based on section 2.2)
    - Chiller's dynamics
- Data Collection (based on section 2.5.1)
    - Requirements of the data
    - Statistical Analysis of the data
- Modelling methodology (based on section 2.5)
    - Model simulation and implementation
    - Model validation and calibration
- Control methodology (based on section 2.3)
    - Optimal operation
    - MPC formulation
    - Validation of MPC solution based on Key Performance Indicators (KPI)
- Integration of modelling and control (based on 2.6.2)
    - Integrated District Cooling Generation (IDCG)
    - Challenges

After proposing the modelling and control methodologies, the performance of the MPC solution is validated using mathematical theorems and proof (based on section 2.6.3). This methodology follows the literature review results in Chapter 2 i.e., modelling and control methodologies are developed that fill the gaps in the current literature of optimal operation of DCG (Figure 13).

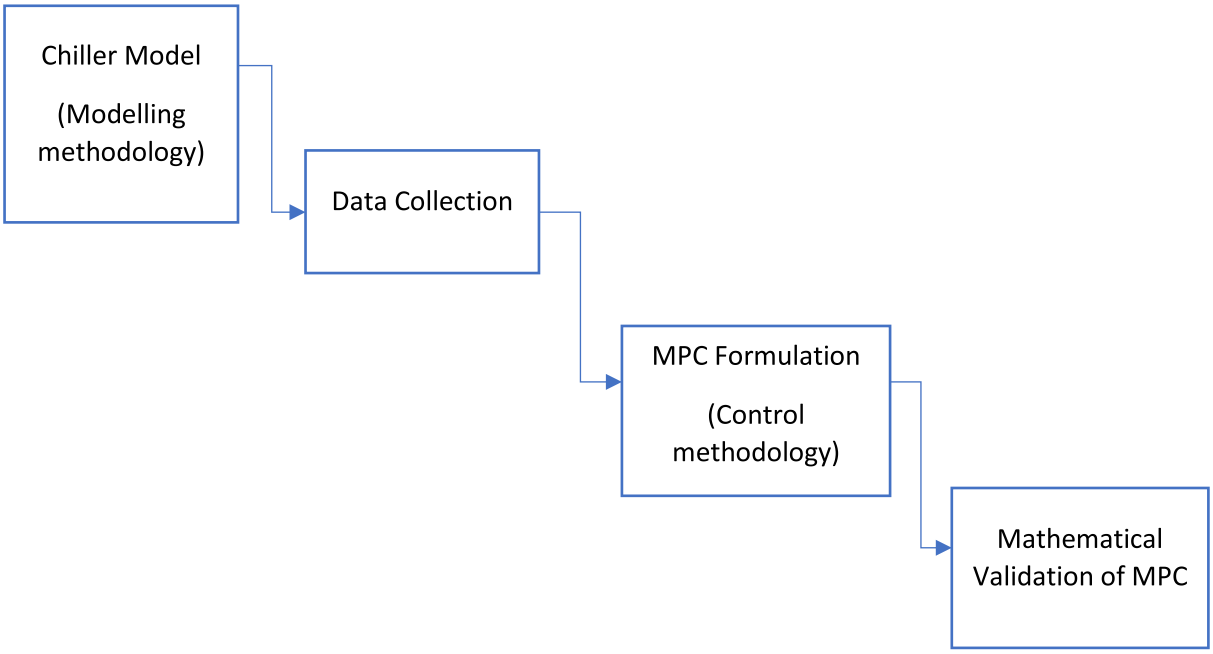


Figure 13: Methodology Flowchart

It is important to note that the type of models derived in modelling methodology and the availability of the data collected at the Basurto hospital leads the flow of methodology to follow a mathematical validation of the control methods. This is discussed in section 3.4 to 3.7.

3.2 Methodology Overview

The methodology of this thesis provides the details of modelling approach starting from the data collection procedure to validation of the simulated models. This process has several steps that are detailed in the sections 3.3 to 3.6 of this chapter.

First, the data is collected from the physical system of **Basurto hospital building**; then, several tools and methods of simulation and modelling and the reason for choosing them is discussed. Second, a predictive control algorithm specific to the needs, issues, and challenges of DCG is developed. At the end, the modelling and control methodologies are integrated as a tool for optimal operation and energy efficiency of DCG.

A comprehensive methodology is presented in this study, which is divided into several sections, as follows:

- Technicalities of DCG: This section elaborates on the engineering aspects of the generation component of DCG.

- Data collection process: This section explains the data collection process and the type of data required for effective DCG control.
- Modelling approach: This section details the development of a prediction model for DCG.
- Tools for simulation: This section outlines the different simulation tools used in the study.
- Model Predictive Control: This section describes the implementation of the MPC algorithm and its constituent building-blocks.
- Integration of modelling and control methodologies: This section explains how modelling and control technologies are integrated into a tool for DCG operation.
- Validation of the developed methodology of integrated modelling and control of DCG: This section validates the proposed methodology through case studies results.

The detailed building-blocks of the methodology are shown in Figure 14. The tools depicted (MATLAB, Modelica) are attached to the block where they are used. In the next sections, the details of each component of this methodology schematic are explained. The methodology starts from implementation of the prediction model by using the data collected from the DCGS, while the optimal operation block gives the set-point for thermal comfort temperature. The result of the prediction model goes into the MPC problem formulation block to calculate the desired controls. The MPC solution is then validated using mathematical validation block and the validated controls are applied to the DCGS.

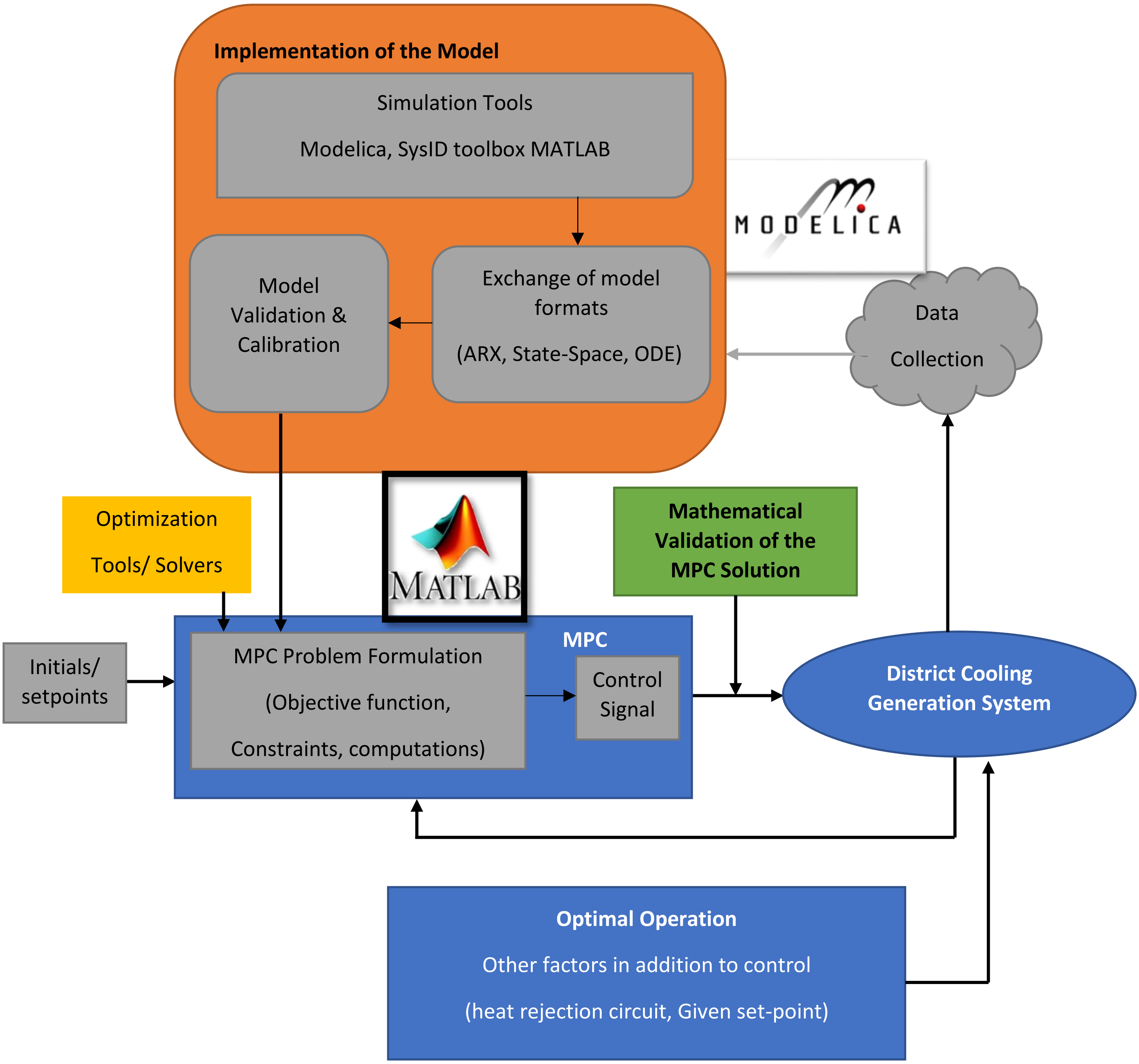


Figure 14: Detailed methodology framework

3.3 Overall Engineering of DCG

To maximize the performance of the DCG, the technicalities of the generation components and how these components are connected to the rest of the DCS are studied. Below, the dynamics and the inner workings of the chiller and cooling tower as the two main parts of the generation component are discussed. The generation plant under study is located inside the Basurto hospital (as part of the EU H2020 INDIGO (2016-2020) project pilot [17]) and includes chillers, storage, pumping, and control. The DC physical plant is a combination of generation plant which is marked by a dark blue arrow and the connected buildings by white arrows in Figure 15.

Figure 15: Basurto hospital DC main layout (Retrieved from INDIGO project [17])

3.3.1 Chiller and cooling tower as a generation system

The chiller and cooling tower are the main components of the DCG. The cooling water goes to the AHU in the building (Figure 16). The detailed working principles of the components are explained in the next sections.

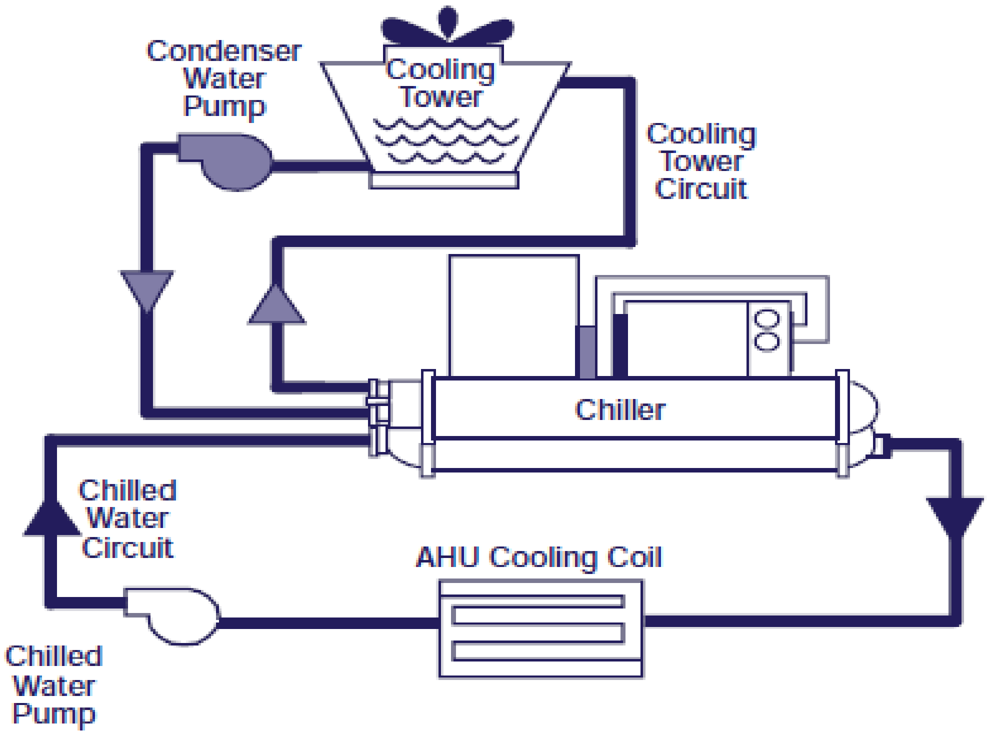


Figure 16: Chiller and Cooling tower in heat rejection circuit (Retrieved from www.energy-models.com).

3.3.2 Chillers

A chiller is a large machine that is used to generate cool water which is used to provide air-conditioning in buildings. Chillers are the most energy consuming components of a DCS (Figure 17).

Figure 17: McQuay chiller in Basurto hospital

There are four parts to the chiller. The inner components of the chiller are as follows:

1. Evaporator is where the “chilled water” is generated; Also, the refrigerant absorbs the heat. The setpoint for the chilled water temperature is given as an input to the evaporator. In addition, this temperature is in a very limited range to avoid the water from freezing. This is one of the main challenges of cooling systems compared to heating.
2. Condenser is the part in chiller where the unwanted heat is collected and sent to the cooling tower; the refrigerant leaves back toward the compressor to continue the evaporation and condensation loop.
3. Compressor is the part where refrigerant is compressed and goes back to the evaporator to continue the cycle.
4. Expansion valve is in the inner loop of the chiller between the condenser and the evaporator. This valve transfers the refrigerant back to the evaporator.

Figure 18 shows the three loops where the chiller is involved:

1. Chilled water loop: The loop where the chilled water from the chiller goes to the building where it is demanded.
2. Refrigerant loop: This is the inner loop of the chiller where the refrigerant is continuously evaporated, condensed, and compressed to cool the adjacent water for the first loop.
3. Heat rejection loop: This is the connection loop between the chiller and the cooling tower. The refrigerant is condensed and leaves its heat to the cooling tower through the condenser.

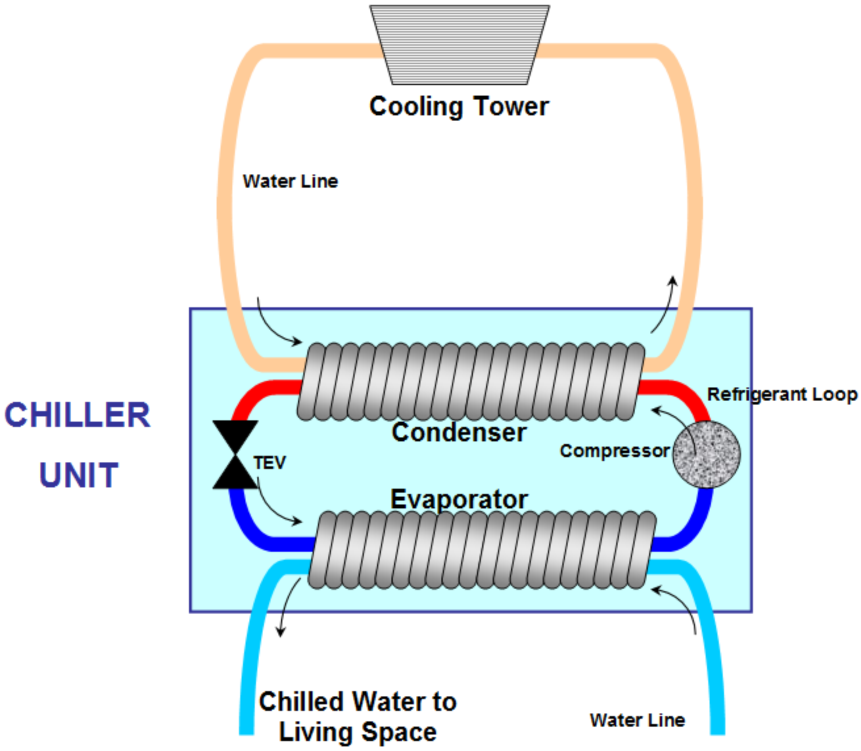


Figure 18: Inner loops of a Chiller (Retrieved from Wikipedia)

The components of the chiller work in the three abovementioned loops and send the cold water to the building where the cooling is demanded.

There are different types of chillers which work with somewhat different principles. The conventional chillers are either water-cooled or air-cooled. Another type of chiller is absorption chiller. Absorption chillers [95] are thermally driven chillers that employ a heat source (hot water, steam, direct combustion, exhaust gas) for producing cold water. Commonly employed absorption chillers are based on a Lithium Bromide (LiBr)-Water working pair where the water acts as a refrigerant (chilled water above 5ºC). Apart from that, these chillers are single stage which means lower temperature for running (hot water as heat source) and lower performance (COP) in comparison with multi stage absorption chillers [109].

3.3.3 Cooling tower

As explained above, the cooling tower is connected to the chiller through the heat rejection circuit. The dry air with specific humidity and flow rate is in touch with the warm water. The dry air collects the heat from the warm water. The warm, moist air dissipates into the atmosphere. The air is blown from the lower part through the tower, and it cools the water sprayed at the top of the tower (Figure 19).

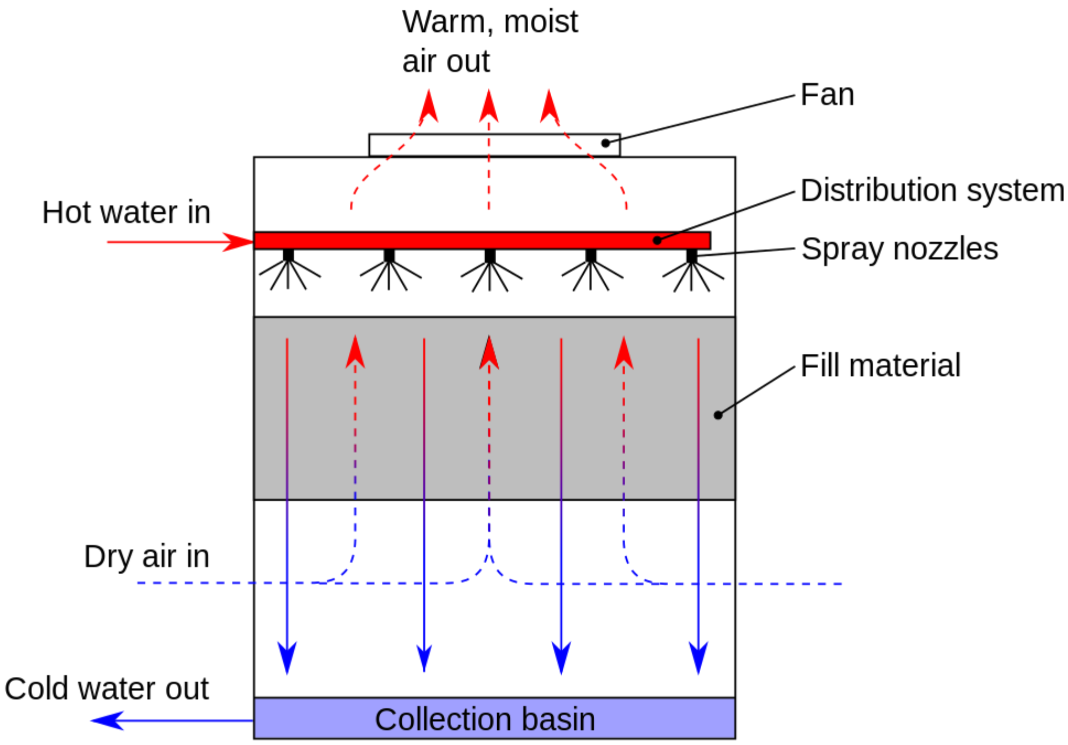


Figure 19: Cooling tower schematic (Retrieved from Wikipedia)

The cold water is collected at the bottom of the tower and sent to the condenser of the chiller unit.

The heat rejection circuit connects the two systems. The warm water goes through the refrigeration cycle in the chiller to get cooled in the inner cycle of chiller. The heat from the refrigerant is dumped through the water that goes to the condenser toward the cooling tower.

3.3.3.1 Complexity of chiller and cooling tower in terms of modelling and control

In this sub-section, the requirements of the DCG models to enable the right choice of tools for modelling and control of DCG are studied.

The thermo-fluid dynamic equations can be used to model the chiller and cooling tower. The modelling is based on the heat transfers in the two following loops in the chiller:

- Refrigeration cycle
- Heat rejection circuit

The heat rejection circuit is the loop between the chiller and the cooling tower. In most cases, there is no direct actuation (control valve) on the cooling tower. Thus, the outputs of the cooling tower are controlled by the desired output signals in the chiller condenser.

3.3.3.1.1 Chiller

To identify an input-output model from the thermo-fluid dynamics in simulation tools, the inputs, disturbances, and outputs of chiller are defined in Figure 20. Notice that Figure 20 is the representation of the chiller input and output without a control loop. Figure 21 shows the variables in the schematic.

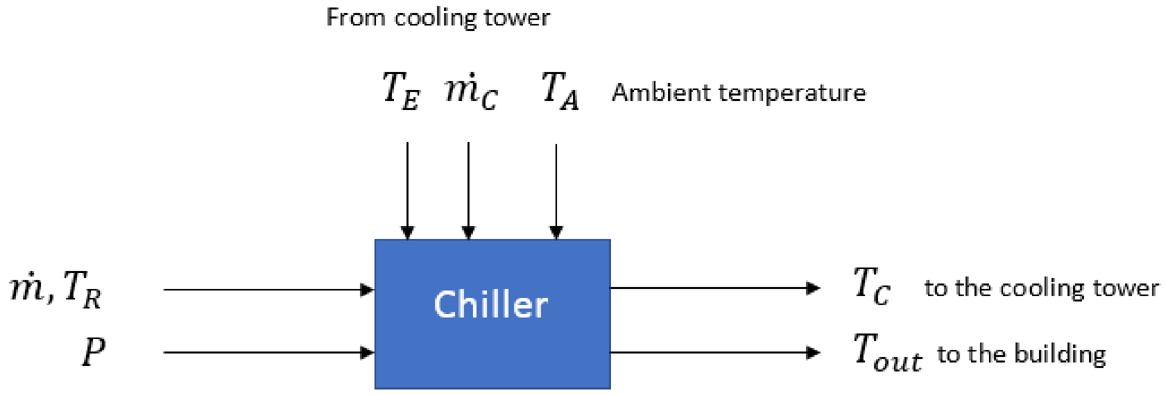


Figure 20: Chiller inputs and outputs without control loop

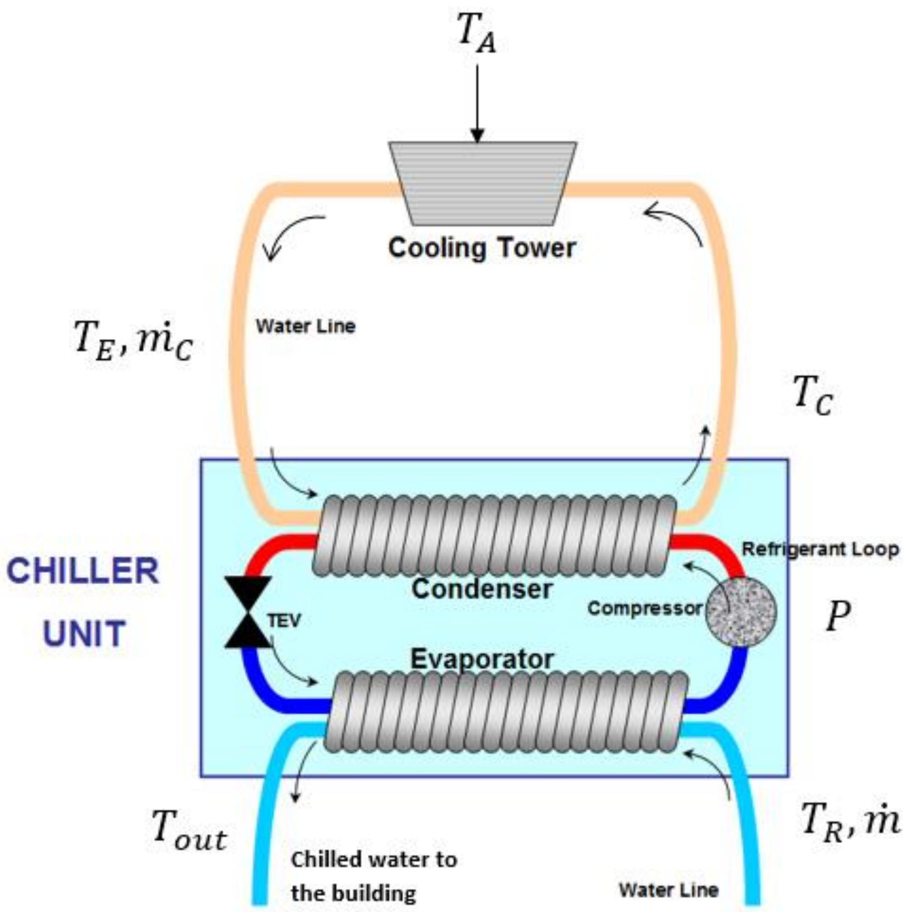


Figure 21: Inputs and outputs of chiller

- Chiller Inputs
    - Evaporator inlet water temperature (T_R, K)
    - Evaporator inlet water mass flow rate $(\dot{m}, kg/s)$
    - Chiller power use (P, W)
- Chiller Disturbances
    - Condenser inlet water temperature (T_E, K)
    - Condenser inlet water mass flowrate $(\dot{m}_C, kg/s)$
    - Ambient temperature (T_A, K)
- Chiller Outputs
    - Evaporator outlet water temperature (T_{out}, K)
    - Evaporator Inlet water Temperature (T_C, K)

The inputs and outputs of the chiller in a control loop are defined in Figure 22.

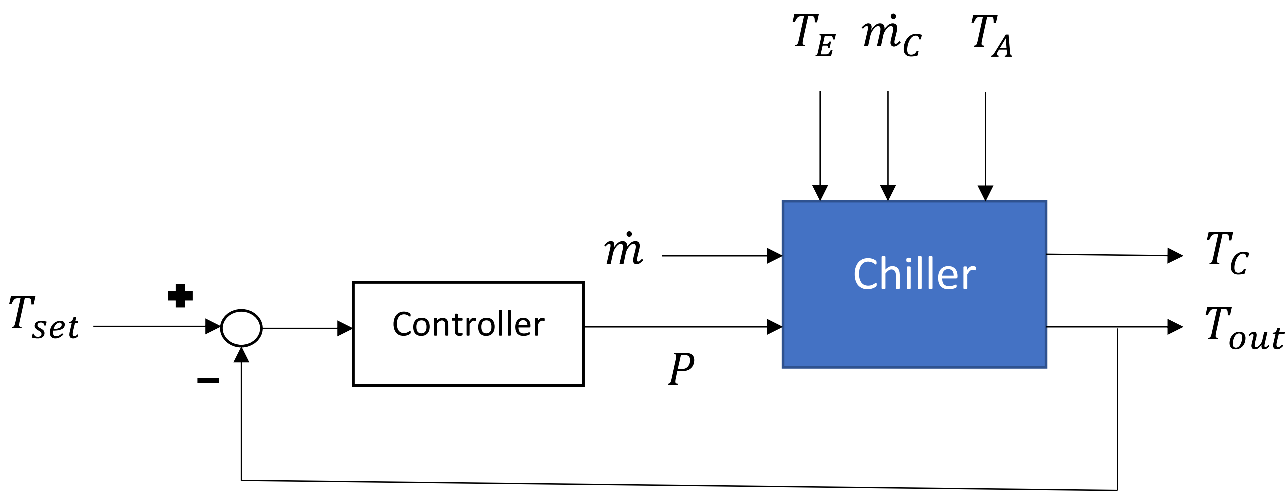


Figure 22: Chiller inside the control loop

- Chiller Inputs in control loop
    - Supply water temperature reference (T_{set}, K)
    - Evaporator inlet water mass flow rate $(\dot{m}, kg/s)$
- Chiller Disturbances

- Condenser outlet water temperature (T_C, K)
- Condenser inlet water temperature (T_E, K)

- Chiller outputs in control loop
  - Evaporator outlet water temperature (T_{out}, K)
  - Power use (P, W)

3.3.3.1.2 Cooling Tower

The inputs, disturbances, and outputs of cooling tower in control loop are shown in Figure 23.

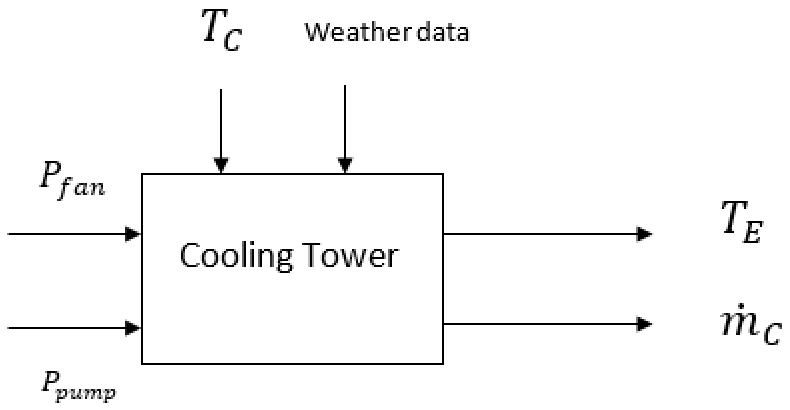


Figure 23: Cooling tower without control loop

The inputs, disturbances, and outputs of cooling tower in control loop are shown in Figure 24.

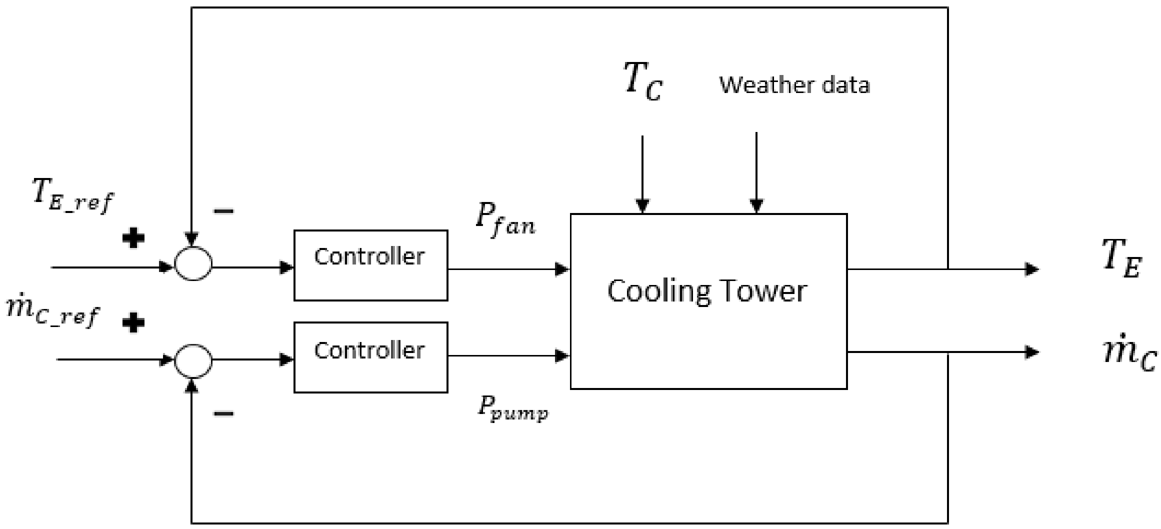


Figure 24: Cooling tower in the control loop

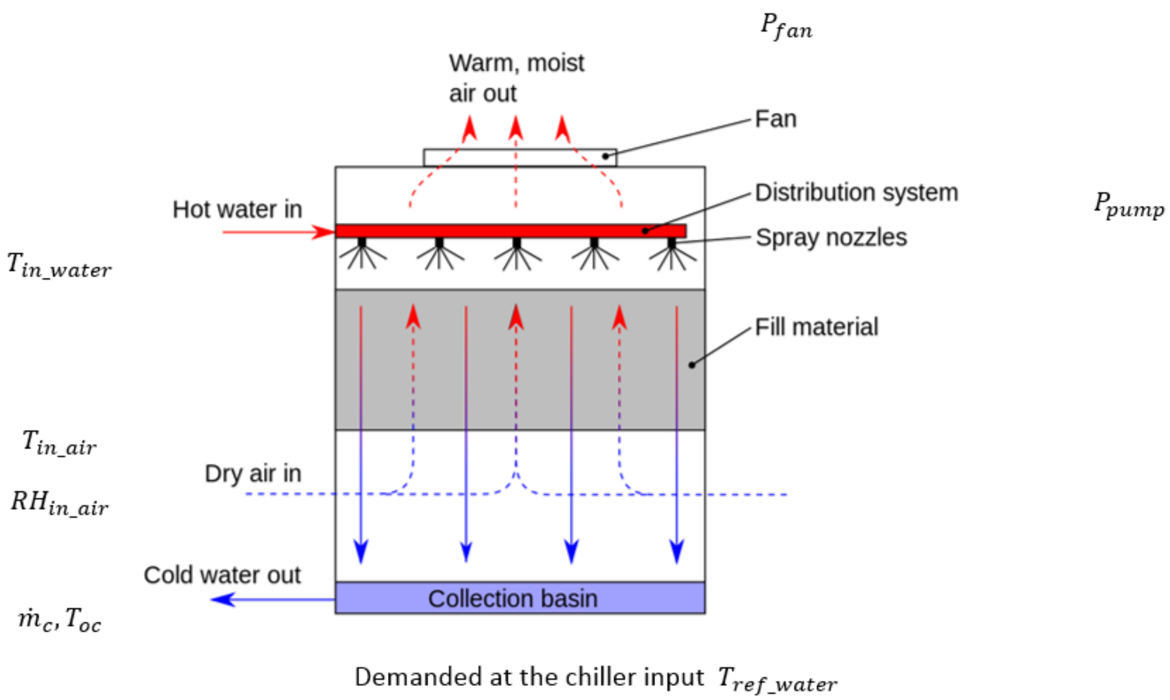


Figure 25: Inputs and outputs of cooling tower

The inputs, outputs, and disturbances according to the variable names in Figure 25 are:

- Cooling tower inputs
  - Inlet flowrate into the condenser ($\dot{m}_c, kg/s$)
  - Set-point temperature of the inlet water from the chiller into the cooling tower (T_{ref_water}, K)
- Cooling tower disturbance
  - Temperature of the inlet water from heat rejection (T_{in_water}, K)
  - Relative Humidity (RH) of the inlet air to the fan (Weather data RH_{in_air}, kg^{-1})
  - Temperature of the inlet air to the fan (Weather data T_{in_air},K)
- Cooling tower outputs
  - Fan power use (P_{fan}, W)
  - Pump power use (P_{pump}, W)
  - Outlet temperature of the condenser (T_{oc}, K)

Both chiller and cooling tower are nonlinear systems, i.e., there is a nonlinear relationship between the outputs and inputs of these systems. Cooling tower is a highly nonlinear system; The number of control inputs is less than the number of degrees of freedom to control the system, i.e., the system is under-actuated. In other words, the operation and efficiency of the cooling tower is highly affected by the ambient temperature and relative humidity. The output of the chiller into the cooling tower cannot be manipulated. The only manipulated variable is the flow rate of the condenser water from the cooling tower into the chiller. Chiller is connected to cooling tower through the heat rejection circuit; Thus, the cooling tower can only be controlled through the chiller.

As a result of these complexities in the generation system, simulation tools are required that can represent the model and the physical complexities of chiller and cooling tower. In addition, the model should be reduced to a form that well represent the physical reality of the system and could be used for the MPC.

The choice of simulation tools requires the following:

- The tool should be compatible with the already-installed tools in the DCG plant in Basurto hospital.
- The ODE solvers should be able to solve the dynamic thermo-fluid equations of the interactions between the DCG components.

In the next section, the data collection for the validation and calibration of the chiller models and control are discussed. This will complete the puzzle of the requirements of the modelling and control approach for DCG.

3.4 Data collection

The data is collected from a real-life application of the Basurto hospital building to examine the effectiveness of the designed MPC methods.

There are specific hardware and software involved in data collection process which we will present their details in the case study chapter. However, we present the data collection methodology in this chapter.

Data collection methodology is developed in the following steps:

- Instruments and hardware for reading the data
- Software for recording the data
- Frequency of the readings and recording of the data
- Statistical analysis of the data

3.4.1 Instruments and hardware

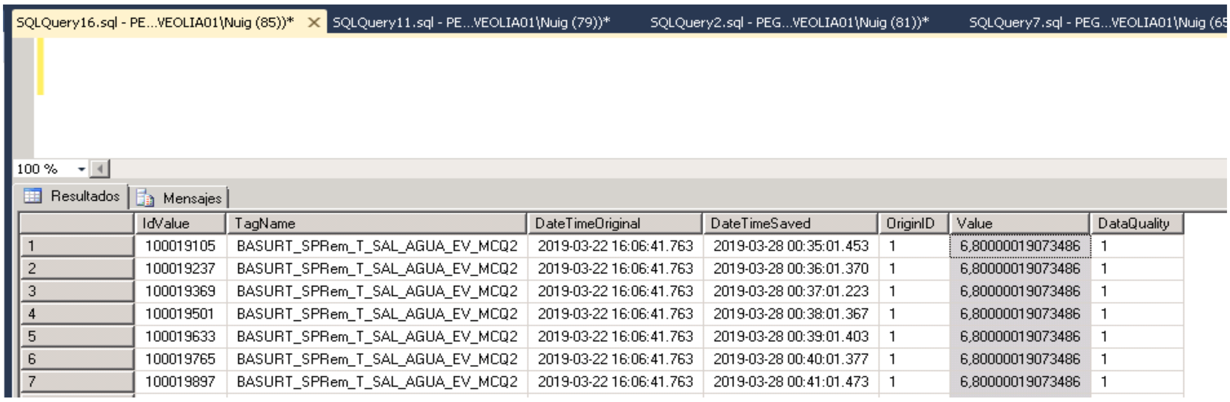
The required input, output, and disturbance signals are presented to the company who is responsible for the instrumentation and hardware installed in Basurto hospital DCG (Veolia).

Veolia then provided some guidelines to connect to the DCG database in Basurto hospital. The details of the software package to extract the data is presented in the case study chapter. The required signals are recorded through installed sensors. Then, the following process in the software package determines if the data is qualified in terms of the collection hardware.

3.4.2 Software Package

The data collection facility in Basurto hospital has a "DataQuality" information column in its Microsoft SQL management database. This column is a reality check to find out if the data is faulty or not (Figure 26). If the value:

- Is zero, then there has been a fault in data collection and data is not reliable.
- Is 1, then the data is reliably measured and recorded.



	IdValue	TagName	DateTimeOriginal	DateTimeSaved	OriginID	Value	DataQuality
1	100019105	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:35:01.453	1	6,80000019073486	1
2	100019237	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:36:01.370	1	6,80000019073486	1
3	100019369	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:37:01.223	1	6,80000019073486	1
4	100019501	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:38:01.367	1	6,80000019073486	1
5	100019633	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:39:01.403	1	6,80000019073486	1
6	100019765	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:40:01.377	1	6,80000019073486	1
7	100019897	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2	2019-03-22 16:06:41.763	2019-03-28 00:41:01.473	1	6,80000019073486	1

Figure 26: Software to record the data

Below, the next piece of data collection methodology is presented, reading and recording the data.

3.4.3 Frequency

Data collection requires a chosen frequency of recording the data by the sensors. The data is collected based on the frequency of the following variables:

- Dynamic changes in the system in time, e.g., the rate of change of the mass flow in the evaporator.
- Frequency of applying a new control signal, i.e., how often a control signal with a new value is applied to the system.
- How chiller and cooling tower as the generation is connected to other parts of the DC system? (The initial values and the setpoints for some variables (T_{set} , $\dot{m}$) come from

the manager level.)

3.4.4 Statistical analysis of the data

The data quality can be compromised either because of the hardware that collects the data, or the software that processes it. In this thesis, the two following measures are set up to ensure the quality of the data that will be later used in the MPC development.

The extracted data is ensured based on the following measures:

3.4.4.1 Errors

Different types of errors can be calculated:

Absolute error

$$Error = f(y_i - \hat{y}_i)$$

Equation 1: Absolute error

Relative error

$$\frac{\sum |y_i - \hat{y}_i|}{n}$$

Equation 2: Relative error

Then, the error values are checked in the simulations. The numerical error values and graphs are presented in the results and discussions.

3.4.4.2 Outliers

After the unfaulty data is separated from the faulty data (using the DataQuality column), there may still some outlier data be present in the data vectors. The outliers are removed using MATLAB function “rmoutliers”, and the associated MATLAB algorithms.

As these two measures have been applied to the data, it is concluded that:

- The six chiller variables (two inputs, two disturbances, and the two outputs) have outliers and faulty measurements at different time steps of the measurement process.
- In addition, most of the variables (two inputs, two disturbances, and the two outputs of the chiller) are missing the measurements for a big range of time (Figure 27). As a result, this data cannot be used to run a *continuous simulation* of the system (unreliability of the data), however this data can still be used to find out the ranges of change of the variables.

This data quality is a major issue which gives a new direction to the methodology.

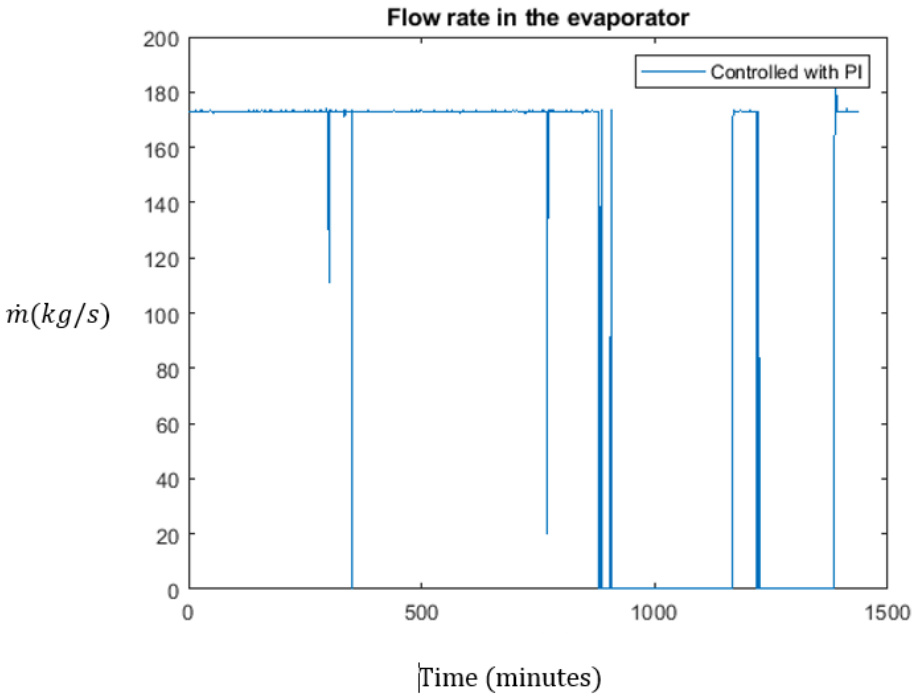


Figure 27: Fault in data measurements or recording (mass flow rate vs time in minutes)

Remark 3.1: This result is the steppingstone to change the methodology of validation of MPC from the traditional case study simulation to a method which is a combination of case study simulations and mathematical validation of the MPC solution.

3.5 DCG Modelling Approach

The purpose of this section is to develop a modelling methodology specific to the challenges mentioned in the literature review and the complexities of generation components. The final goal of modelling methodology is to generate the **prediction models** for MPC of DCS.

3.5.1 Requirements of the Model

What are the requirements of the model to be used in DCG control?

The final goal of this thesis is the predictive control of DCG. Therefore, the needs of control in terms of models are considered here. MPC requires the estimation of the state at every sampling instant for the discrete-time simulation of the DCG.

3.5.2 State Estimation

The estimation of the states is available through one or combination of the following methods:

1. State estimation methods such as Kalman Filter [101] or Moving Horizon Estimation (MHE) [81], [83].
2. Estimation through direct measurements of the data [22].

The first method is generally used when there is no access or partial access to actual physical data. The second method is fit to the systems that have actual physical measurements and the purpose of the model is to set up a control on a living lab or an application.

In this methodology, the estimation of the states come from the measurements collected at the case study building. This is because there is access to the data from Basurto hospital. Furthermore, **the state estimation from the state space models** is used to compensate for the unreliability of the data.

In this thesis, state feedback MPC is considered which means that exact knowledge of the system state is assumed. From a practical point of view, this implies that any errors that are introduced by a state estimator (used to estimate the states based on output measurements) are assumed to be sufficiently small and are hence neglected.

The available data from DCG plant is described in the form of an input-output model at a sampling time that can capture the dynamics of the system. The *sampling time and the type of model* are two factors that affect the modelling results (discussed below in further details).

3.5.2.1 Sampling time

In Basurto, the DCG is operating and generating continuous values for the inputs and outputs of the DCG. However, the data measurement devices installed on the case study building have their own sampling time to read and record the measurements.

The system dynamics in continuous-time is observed. The dynamics are important in choosing the appropriate sampling time for both the *measurement readings* and *discretization method* in the simulation tools.

Some systems are fast, meaning the input-output relationship is changing in a matter of milliseconds, e.g., an inverted pendulum. However, the DCG which is studied in this thesis is a slow system, i.e. the input-output relationship changes in a matter of 5-15 minutes.

The choice of sampling time also affects the *computational complexity*; The lower the sampling time, the higher the computational burden of solving the MPC problem. One requirement for the DCG models for MPC is that they provide the states with *lower computational complexity*.

3.5.2.2 Types of Models

3.5.2.2.1 Equation based models

3.5.2.2.1.1 Auto-Regressive Exogenous

Linear systems are considered whose dynamics can be represented by Auto-Regressive Exogenous (ARX) models of the form

$$y_k = \sum_{i=1}^{n_y} a^i y_{k-i} + \sum_{j=1}^{n_u} b^i u_{k-j}$$

Equation 3: ARX model

In Equation 3, $y_k, u_k \in \mathbb{R}$ denote respectively the model output and input at time k. Coefficients $a^i, i = 1, \dots, n_y$, and $b^j, ji = 1, \dots, n_u$ are the parameters of the system. According to equation (1), the output at time k depends on the previous n_y outputs and n_u inputs through the parameters a^i, and b^j.

3.5.2.2.1.2 State Space Representation (SSR)

ARX represents the relationship of each output with inputs and outputs in previous time steps, However, State Space Representation (SSR) represents the relationship between the input and outputs of the system in explicit equations. For the explicitly represented equations, SSR are favourable compared to ARX models in this application.

In this thesis, the equivalent SSR of the ARX model [110] is used. It is more convenient and common to formulate the MPC problem using the SSR due to the explicit relationship of the consecutive states; It can easily be simulated in various simulation tools as most coding structures prefer an explicit relationship. In the following sections, the discrete-time linear state space model is used.

3.5.2.2.2 Data-driven models

ARX models is changed into SSR using the algorithm explained in [110] or MATLAB System Identification toolbox. The development of a virtual test-bed for MPC has been discussed in [111], [112]. These developments of the partners in EU H2020 INDIGO (2016-2020) project [17] are models of generation system that are driven from the input-output data (data-driven models). The virtual test-bed developed in collaboration with the authors of [111], [112] from EU H2020 INDIGO (2016-2020) project is used as the basis for the prediction models of this thesis.

3.5.3 Modelica Models

In this subsection, the role of Modelica models in the process of modelling and control of DCG is explained. The results of this modelling methodology are also published in [112].

Modelica models are the detailed nonlinear representation of the physical system behaviour and dynamics, also a connection from the real world to the simulation tools. The main benefit of Modelica models is that the equations can be coded *explicitly* in Modelica. Basically, the thermodynamic equations for the heat exchanges in chillers and cooling towers are coded exactly as they are written as ODEs in continuous time. Additionally, Modelica offers two options for modelling DCS components: pre-defined elements such as pumps and fans that can be accessed through a graphical user interface, or writing equations based on heat exchange principles in chillers, cooling towers, and heat rejection circuits. The internal control of the systems can also be included with their respective equations. The Annex 60 library and buildings library for building and district energy systems [34] is used in [112] for pre-defined elements of DCG.

The physical system of DCG consist in different components like sensors, valves, and pumps; These are all included in Modelica models. The Modelica models generated in EU H2020 INDIGO (2016-2020) DCOL [113] are validated using the real data from the system of chiller and cooling tower. However, these models are not still ready to be used in MPC because of its high computational complexity. This model should be simplified to a lower-complexity equation-based model or serve as a foundation for developing data-driven models [111]. However, the Modelica model is used for the following purposes:

- Generation of virtual input-output data
- Validation data for the reduced model

In summary, the detailed Modelica models are used to generate the validation data. In addition, these models are used as the basis to generate the reduced models in the SSR format [112].

3.5.4 Prediction model

Prediction model is the model that is used in MPC to predict the output at the current time step for the whole *prediction horizon*. The MPC solution (to follow the reference trajectory) yields the control action based on the minimizing the error between reference and control variable. The control action is applied to the prediction model to generate the next control variable; The loop then continues at every new time step according to Figure 28 [114]. At each simulation time, the MPC controller solves an optimisation problem to determine the optimal control action for the next time step based on the current state of the system and the predicted future behaviour of the system. This process is repeated at each time step to update the control input as the system evolves. In this way, the MPC controller adjusts the control inputs in real-time to ensure that the system is operating as desired.

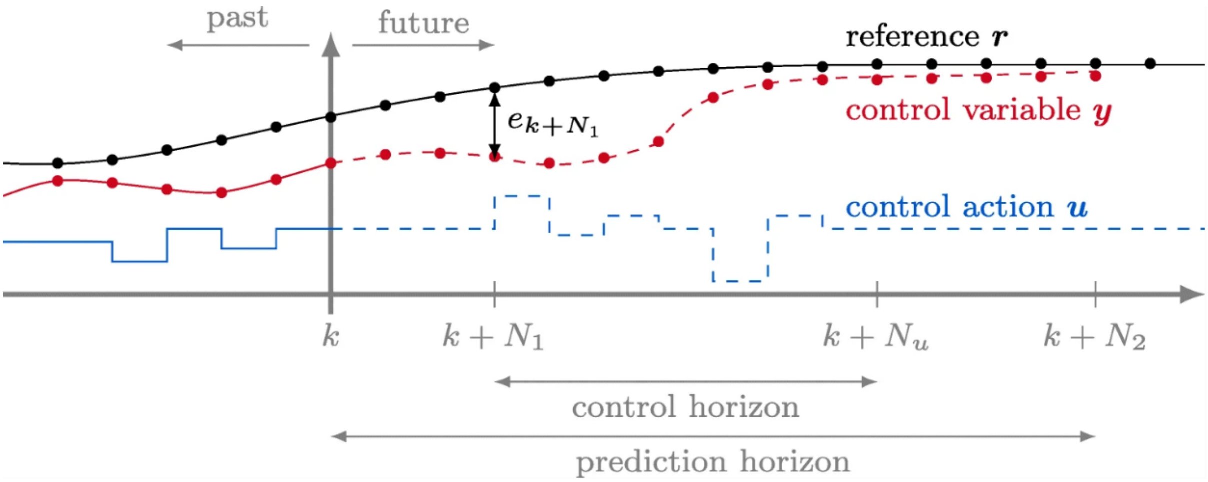


Figure 28: MPC prediction model

3.5.4.1 Choosing the Prediction model

There are several points to consider in choosing the prediction model:

- The model should be able to provide the (control and output) predictions for the MPC.
- The type of model affects the computational complexity of the MPC problem.
- The prediction model affects the solver that is used to solve the MPC problem.
- The prediction model can be a state space model that is already identified (before the control process starts) or re-calculated in each time step (Moving Horizon Estimation).

Considering the complexities of the DCG mentioned in section 3.3.3.1, a fixed validated model is chosen for the predictions. So, the prediction model is the resulting state space model in [112].

The Linear-Time-Invariant (LTI) state space models are presented as

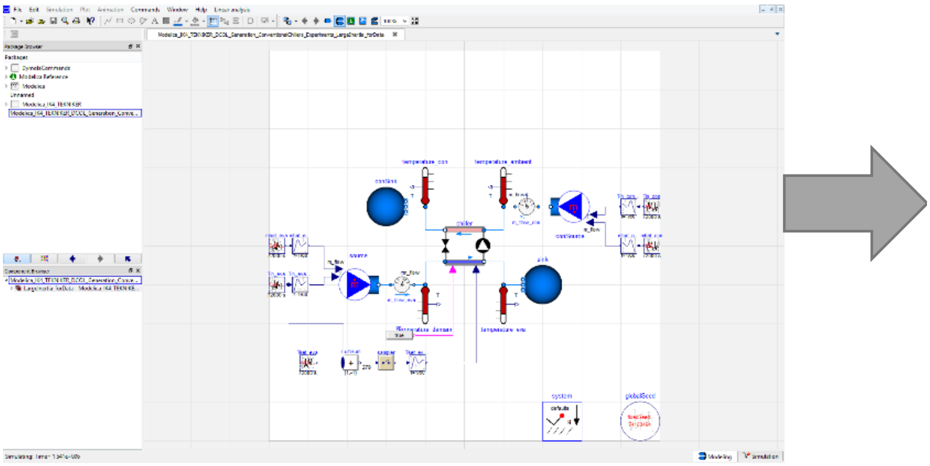
$$\dot{x} = Ax(t) + Bu(t)$$

$$y = Cx(t) + Du(t)$$

Equation 4: State space model

In Equation 4, $x \in R^n$ and $u \in R^m$ are the state vector and the input vector respectively with dimension n and m in the space of Real numbers R, and $A \in R^{n\times n}$, $B \in R^{n\times m}$, $C \in R^{m\times n}$, and $D \in R^{m\times m}$ are matrices of mentioned dimensions in the space of the Real numbers. In the second equation, y is the output of the system. There is a linear relationship between the states x and its derivatives. In addition, the matrices A, B, C, D are invariant in time. That is the reason this model is called LTI.

The state space model for the chiller in the case study of this thesis was generated according to [111] (Figure 29).



$$\dot{x} = Ax(t) + Bu(t)$$

$$y = Cx(t) + Du(t)$$

Figure 29: Generating an SSR from the Modelica model

3.6 Control Methodology

In the literature review of this thesis, the available control methods that have been used in the control of DCS are studied. In this section, the focus is on the MPC. Classic optimal control method solves one optimisation problem to find the optimal value for the control variables over an infinite horizon and then applies this control input for the whole finite duration of the problem. This means that if the system has any uncertainty, it can only be dealt with once and in one optimisation problem. As a result, these methods are not adaptive to changes in the system, nor robust to the uncertainties that may arise. However, in MPC, the optimisation problem is repeated every sampling time, so if any disturbance arises in the duration of the operation of the system, or if there is a fault that detected at any point, the disturbance or the fault can be adapted accordingly. This inherent adaptive feature of MPC makes it very useful and efficient especially in the operation of slow and industrial processes and applications.

MPC methods were proposed and implemented for the DCG of Basurto hospital. During the development of the control methods, it was ensured that:

- The internal and installed control of the physical system is not interfered with.
- The control method can be implemented online and in real-time for the case study

without requiring high computational capacity.

3.6.1 Model Predictive Control

MPC solves an optimal control problem while predicting the future behaviour of a dynamic system on a finite time horizon based on the current state measurement [81]. The corresponding optimal control input is then applied to the real process until the next measurement arrives and the process is repeated. MPC relies on the dynamic models of the system and these models are used to predict the behaviour of the system in the next sampling instant (prediction model).

The implementation of such controllers is based on having an accurate system model; that is, the future of the system is optimized as if there were neither external disturbances nor model-plant mismatches present, although these disturbances and model inaccuracies are the only reason why feedback is needed at all. The main advantage of this assumption is that the corresponding online optimisation problems can often be solved efficiently and in real time [115]. The prediction model for the MPC has already been discussed in section 3.5.4. The subsequent sections explain the fundamental components of the MPC problem.

3.6.1.1 Optimisation Problem

The purpose of the MPC controller is to solve an optimisation problem to get the feedback control $u_k = \mathcal{K} x_k$ at each sampling instant k for the states to track a set-point x_{ref}. The input values are adjusted towards the reference values, denoted as u_{ref}.

3.6.1.1.1 Objective function

The MPC formulation is based on solving an optimisation problem with a goal which can be minimize/maximize the value of the function. The performance of this optimisation is validated by observing the decrease/increase of consecutive function value. Calculating the value of the objective function is called function evaluation in the optimisation theory [104]. The complexity of solving the optimisation problem is usually defined by the number of function evaluations at each operating point.

This equation represents a quadratic objective function.

$$minimize \quad \sum_{k=0}^{N-1} \left(x_k - x_{ref}\right)^T Q \left(x_k - x_{ref}\right) + \left(u_k - u_{ref}\right)^T R \left(u_k - u_{ref}\right)$$

Equation 5: MPC generic objective function

In Equation 5 N is a prediction horizon, and Q, R are the weighting matrices for the states and inputs respectively; x_k is a vector which shows the values of states at time k; u_k is a vector that shows the value of input at time k and the size of ; u_k corresponds to the number of control variables; R is a square matrix and its size equals the number of inputs.

In the DCGS application, the two goals are:

- Minimize energy use.
- Track the desired Temperature set-point (defined by T_{set}) based on the demand from manager level.

The cost function is defined as:

$$\mathrm{q} * \ (T_{out}(t) - T_{set}(t))^2 + r * (P(t) - 0)^2$$

Equation 6: Objective function of DCGS application

In Equation 6, $T_{out}(t)$ is the water outlet temperature of the evaporator, $P(t)$ is the power use in the chiller, and q, r are the weights of temperature error and power use respectively.

3.6.1.2 Constraints

The constraints in the optimisation problem are state constraints, input constraints, and the output constraints $x \in X, u \in U, y \in Y$. Constraints may arise due to limitations or saturation in the control devices of the physical system. Since the exact state knowledge is available (assumption in section 3.5.2), the output constraints can be represented using the output state relation in ARX or SSR.

3.6.1.3 MPC Algorithm Implementation

MPC solves an online optimisation problem in finite-horizon at every sampling instance. The optimisation is formulated to be solved in the interval $[k, k + N]$ where k is the current time and N is the prediction horizon of the optimisation problem. The first resulting control input from the optimisation is usually applied to the system at current time and the rest of the input sequence is discarded. The optimisation process is repeated at each subsequent sampling time until the desired objectives are achieved and the system reaches stability [116]. The algorithm can be summarized in the following steps:

1. Measure the current state at time k (Measure $\mathrm{x_k}$) based on the model.
2. Generate the objective function and constraints.
3. Solve the optimisation problem and find the optimal control input sequence (u_k^*).
4. Apply u_k^* and discard the rest of the optimized input sequence.

5. Repeat steps 1 to 4 until the system reaches stability and the desired objectives are achieved.

The graph in Figure 30 is a general configuration of an MPC loop to control the DCG. The set-points of variables and the initial values of the parameters of the generation system are set in the block of "Setpoints/initials" from a higher manager level. This information is then given to the MPC-controller block.

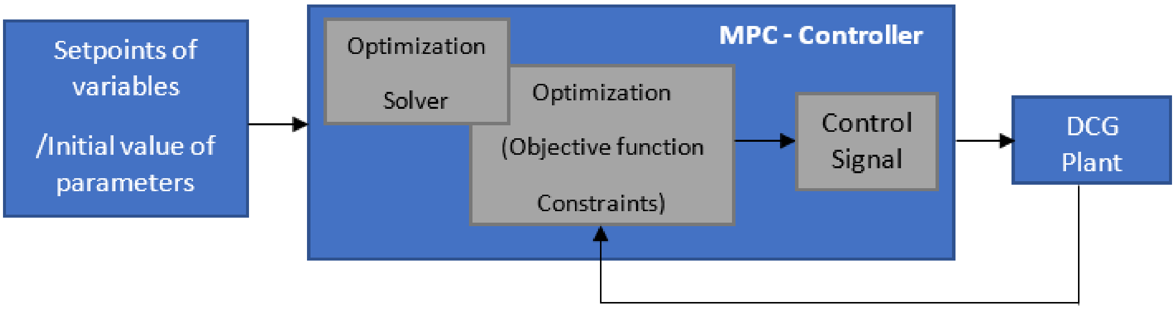


Figure 30: MPC Feedback Control Loop

The controller block follows these steps:

The result for the values of the control signal (u_k^*) is given to the DCG plant through the arrow which goes from the controller block to the DCG plant. This optimal value of control signal is applied to the DCG plant in its block. The state and output values are recorded and fed back to the controller block as the previous values of the states. The arrow from the plant back to the controller shows this feedback. This feedback constitutes a closed loop system for calculating and validating the control signal which is called Control Loop in system control theory [81].

Solvers

Considering the structure of the cost function and the constraints, the problem is a Quadratic Programming (QP) problem. Although there are numerous solvers available for solving QP problems, not all of them can meet the computational demands and constraint handling requirements of the generation MPC in this case study. The data and set-point values are extracted and entered at every single sampling time in real-time which requires high computational capacity for the solver and the optimisation modelling system. This is also a trial-and-error issue that different QP solvers are used, and the information of the optimisation problem is looked at (speed of solving, hessian matrix of the optimisation, how much the cost function is minimized at each step of the optimisation). This information is discussed in the result chapter of this thesis.

3.6.1.4 Timings

3.6.1.4.1 Sampling Time

Although the data is recorded every second, it is resampled according to the needs of the modelling or control algorithm. The sampling time of the optimisation problem is the time between the two consecutive optimisation problems in the MPC optimisation loop. This variable needs to be chosen in a way that considers the dynamics of the system (how fast/slow it is) and the intervals that the cost function is evaluated.

Another important thing to consider is the sampling time of the discrete-time model. A sampling time is used to discretize the continuous-time model. The sampling time of the optimisation problem needs to be compatible with this later.

3.6.1.4.2 Horizon

The horizon of the MPC problem is the interval that each optimisation problem is solved at. This variable needs to be long enough to consider the changes in the behaviour of the system dynamics (oscillations, instability), and short enough to reduce the computational burden of solving a large Quadratic Programming with many variables.

The control horizon is the duration for which the control signal is computed, while the prediction horizon is the duration for which the simulation is performed. In current MPC practice, the control horizon is commonly set equal to the prediction horizon, and the general term 'horizon' is used to refer to both.

3.7 Mathematical Formulation of MPC

Following the steps mentioned in the modelling and control methodology, the MPC problem is formulated for efficient operation of DCG as below:

$$\text{Minimize} \quad \sum_{t=0}^{N-1}\{q * (T_{out}(t) - \underline{T_{set}}(t))^2 + r * (P(t) - 0)^2\}$$

$$\text{Subject to} \quad \dot{x} = Ax(t) + Bu(t) + Ev(t)$$

$$y = Cx(t) + Du(t)$$

$$u(t) = \begin{bmatrix} T_{set} \\ \dot{m} \end{bmatrix}, v(t) = \begin{bmatrix} T_E \\ T_C \end{bmatrix} \quad , y = \begin{bmatrix} T_{out} \\ P \end{bmatrix}$$

Basurto Data

$$\boxed{\begin{array}{l} T_{min} \leq T_{set} \leq T_{max} \\ \dot{m}_{min} \leq \dot{m} \leq \dot{m}_{max} \\ 0 \leq P \end{array}}$$

Equation 7: MPC problem formulation

In Equation 7, the term $Ev(t)$ is added to the states equation to represent the disturbances (to separate the disturbances from the inputs). The $v(t)$ is the disturbance vector at time t, and E is a matrix that represents the relationship between the states and the disturbances.

The different components of the MPC formulation are explained below:

- The water temperature values are subject to upper and lower bound constraints ($T_{min} \leq T_{set} \leq T_{max}$), which are derived from the Basurto data.
- The mass flow rate of the chilled water supply is subject to upper and lower bound constraints ($\dot{m}_{min} \leq \dot{m} \leq \dot{m}_{max}$), which are based on the Basurto data.

The six variables of the chiller are measured and used as inputs to the MPC formulation, linking the real-life application to the control approach. However, as discussed in section 3.4.4, the reliability of the data varies among the different variables in the Basurto database. Furthermore, the quality of the Basurto dataset does not permit a continuous case study to be conducted. Therefore, it has been decided to solve the MPC problem explicitly using optimisation algorithms. Additionally, the literature on the theoretical solution of MPC has been reviewed in chapter 2.

3.7.1 Optimisation Methods to Solve MPC

In this section, a solution to the MPC problem is presented using optimisation methods. This method analyses the MPC problem from an equation-based mathematics problem and identifies an explicit solution based on **optimisation theory** and techniques [104]. In order to analyse the performance of the MPC problem, the authors in [101], [103], [117] take a mathematical approach to show that **an explicit optimal solution exists** for the system under study. In this section, a similar approach is considered to show that an explicit solution for the chiller MPC exists and can be derived using optimisation theory.

The idea is to solve the MPC problem using the optimisation methods and find an explicit solution to the optimisation problem above. According to the measured and estimated data from the hospital and models, we know that the decision variables are in specific ranges of values. The data is then collected in the case study and the bounds of the variables are tested to be in the stability range according to the mathematical derivation below.

The first problem is called "MPC" and the second problem is called "QP" in Equation 8.

$$\text{Minimize} \quad \sum_{t=0}^{N-1}\{q * (T_{out}(t) - T_{set}(t))^2 + r * (P(t) - 0)^2\}$$

$$\text{Subject to}$$

$$\dot{x} = Ax(t) + Bu(t) + Ev(t)$$

$$y = Cx(t) + Du(t)$$

$$u(t) = \begin{bmatrix} T_{set} \\ \dot{m} \end{bmatrix}, v(t) = \begin{bmatrix} T_E \\ T_C \end{bmatrix} \quad , y = \begin{bmatrix} T_{out} \\ P \end{bmatrix}$$

$$T_{min} \leq T_{set} \leq T_{max}$$

$$\dot{m}_{min} \leq \dot{m} \leq \dot{m}_{max}$$

$$0 \leq P$$

$$p^* = \text{minimize}_{w \in R^n} \qquad c^{\mathrm{T}} w + \frac{1}{2} w^{\mathrm{T}} F w$$

$$\text{Subject to} \quad Gw - b = 0$$

$$Hw - d \geq 0$$

Equation 8: Equivalent representation of MPC problem into a QP

If the QP problem is a convex problem, then its explicit solution can be derived using the "strong duality" [104]. The mathematical solution of a generic QP is already found and the method is explained in the literature. So, if an equivalent representation of the MPC problem into a QP is found, the explicit solution of the MPC problem will also be available.

Remark 3.2: The main objective is to redefine the decision variables of the MPC problem and formulate it as a QP that can be solved.

3.7.2 Mathematical Derivation of Explicit Solution

The optimisation problem is solved as follows:

1. The state space model of the system in differential continuous form is linearized using Euler method in Equation 9.

$$\dot{x} = \frac{x(k+1) - x(k)}{\Delta t}$$

Equation 9: Estimation of derivatives using Euler method

and yields the Equation 10:

$$\begin{array}{c} \dot{x} = Ax(t) + Bu(t) + Ev(t) \\ y = Cx(t) + Du(t) \end{array} \quad \Longrightarrow \quad \begin{array}{c} x(k+1) = Ax(k) + Bu(k) + Ev(k) \\ y(\mathrm{k}) = Cx(k) + Du(k) \end{array}$$

Equation 10: Linearization of state space model

A linear discrete-time approximation of the system equations is considered.

2. The Dual problem [104] of the discrete time problem is formulated by constructing the dual of the standard QP:

If the Primal problem is a convex Quadratic Programming, then $p^* = d^*$ [104].

The following variables are redefined in Equation 11:

$$z(k) = \begin{bmatrix} T_{set}(k) \\ \dot{m}(k) \\ T_{out}(k) \\ P(k) \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix}$$

Equation 11: Redefining variables

Thus, the cost function translates into Equation 12:

$$\sum_{k=0}^{N-1}\left\{\mathrm{q} * \left(T_{out}(k) - T_{set}(k)\right)^2 + r * (P(k) - 0)^2\right\}$$

$$= (z_3 - z_1)^{\mathrm{T}} q (z_3 - z_1) + z_4{}^{\mathrm{T}} r z_4$$

$$= \mathrm{q}(z_3 - z_1)^2 + r z_4{}^2$$

$$= \mathrm{q}(z_3)^2 - 2q z_3 z_1 + \mathrm{q}(z_1)^2 + r z_4{}^2$$

$$= [z_1, z_2, z_3, z_4]\begin{bmatrix} q & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -2q & 0 & q & 0 \\ 0 & 0 & 0 & r \end{bmatrix}\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix}$$

Equation 12: Cost function in redefined format

and the constraints are translated to Equation 13:

$$x(k+1) = Ax(k) + Bu(k) + Ev(k)$$

$$y(k) = Cx(k) + Du(k)$$

$$-T_{set} \geq -T_{max}$$

$$T_{set} \geq T_{min}$$

$$-\dot{m}(t) \geq -\dot{m}_{max}$$

$$\dot{m}(t) \geq \dot{m}_{min}$$

$$P \geq 0$$

Equation 13: Constraints in redefined format

3. Using the results from strong duality, the primal optimisation is solved by finding the explicit solution to the dual problem that is redefined by the cost function and constraints in Equation 12 and Equation 13 respectively [104]. Matrices of the primal problem are redefined in Equation 14:

$$c^{\mathrm{T}} = [0 \quad 0 \quad 0 \quad 0]$$

$$F = \begin{bmatrix} q & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -2q & 0 & q & 0 \\ 0 & 0 & 0 & r \end{bmatrix}$$

$$\mathrm{G} = \begin{bmatrix} F & 0 \\ 0 & G \end{bmatrix}$$

$$b = -x(k+1) + Ax(k) + Ev(k)$$

$$H = \begin{bmatrix} -1 & -1 & 0 & 1 \\ 1 & 1 & 0 & 0 \end{bmatrix}$$

$$d = \begin{bmatrix} T_{max} & \dot{m}_{max} & 0 & 0 \\ -T_{min} & -\dot{m}_{min} & 0 & 0 \end{bmatrix}$$

Equation 14: Redefined matrices of primal problem

This redefinition of variables gives an explicit solution to the generic chiller MPC problem under the following circumstances:

- The Hessian of Matrix F is positive semi-definite: F ≥ 0 (essential feature for convexity)
- The constraints are linear equality and inequality equations of the optimisation variables.
- The cost function is quadratic.
- The problem is thus convex, quadratic and has an explicit solution.
- A Piecewise affine (PWA) discrete-time approximation of the system equations is considered.
- The Disturbance can be either measured or estimated.
    - For the chiller, all data collected from Basurto are measurements.
    - The data from simulation of the Modelica model is estimated.
- CPU power for computing QP and memory for storing the explicit solution is needed.

These requirements are examined for the chiller problem in the next chapter.

3.8 Integrated District Cooling Generation (IDCG) Methodology

The modelling and simulation of DCG, the corresponding tools, MPC, and how to formulate an MPC solution for DCG are discussed. However, the modelling and control methods need to work for a single DCS and be compatible with each other. The integration requires that the modelling and control sampling times be compatible in the MPC algorithm and MPC runs in real-time. In addition, the model should provide the predictions for MPC. In this section, the modelling and control methodologies are integrated for DCS. The result is a united framework toward modelling and control of DCS as demonstrated in Figure 31. Figure 31 shows the relationship between each group of the methodologies developed in this thesis. The data of the variables and parameters of DCG are shown as a cloud inside the DCS. The modelling methods receive the information of the plant. The DCS plant performance is feedback for the control method and the control methodology gives the control signal to the plant. This whole configuration contributes to the energy efficiency and optimal operation of DCS.

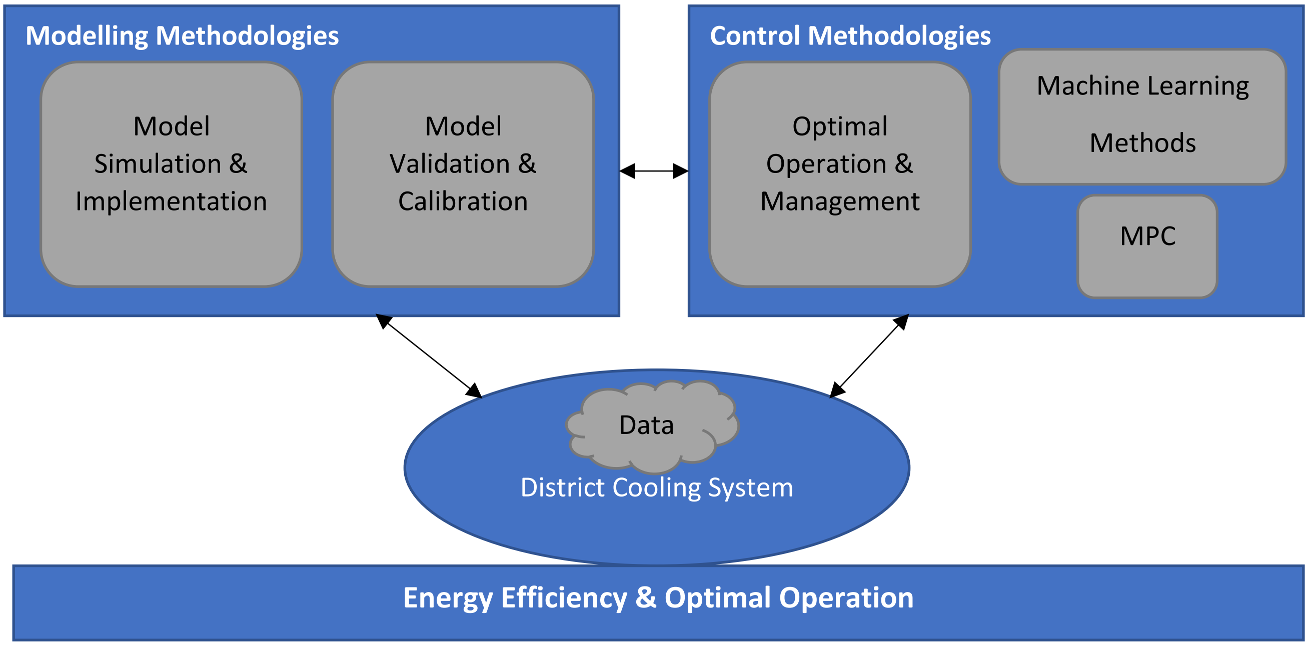


Figure 31: Integration of modelling and control methodologies in DCS

This methodology combines the modelling methodology that is performed in the first block with the control methodology that is implemented in the third block. As highlighted in the literature review chapter, the integration of modelling and control of DCG presents one of the primary gaps in the literature. This integration is faced with several challenges:

- Simulation platform that can represent the model and the physical complexities of DCS.

- Different optimisation solvers used for solving the MPC or the operation management optimisation. The solvers are not necessarily tailor-made for DCS applications and need to be adapted in simulations.
- Big data in operation of the district. The issue can be addressed by real-time MPC; This method receives the DCS data at every sampling time. This prevents the need for a long-term memory to save all the data.
- Recording the values of the cool generation components at every second and looking at the significance regarding the changes in the dynamics.
- Uncertainty in DCS. Liao et al. [65] introduced methods to enhance robustness of a chiller against uncertainties. Uncertainties in a DCS may arise from various sources, including inaccurate load calculations, deviations from the actual layout of the network and buildings in the model, and errors in the modeling and control methods used. For instance, uncertainties in the load calculations may arise from incorrect assumptions or data input, while discrepancies in the layout of the network and buildings may stem from variations in the actual physical environment compared to the simulated model. Additionally, errors in the modelling and control methods may arise from approximations, simplifications, or assumptions made in the model or control algorithm. It is important to handle these uncertainties and ensure a robust performance for the DCS. MPC offers an inherent robustness due to solving an optimisation at every sampling instant, however, robust control techniques need to be studied. This challenge is an area for further research in DCS.

3.9 Conclusions

This chapter is the methodology for DCG modelling and control based on the gaps identified in the literature. This methodology is composed of some of the already existing methods in the literature and adapting and developing a method by extending the concepts to the DCG.

Figure 32 presents the relationship between DCS plant and modelling and control of DCS. The data of DCS is given to the simulation and validation of modelling methodology, and the model is updated based on real-time data from the system. The control technique receives the data and the model for predictions. The control method can act real-time based on the feedback received from DCS.

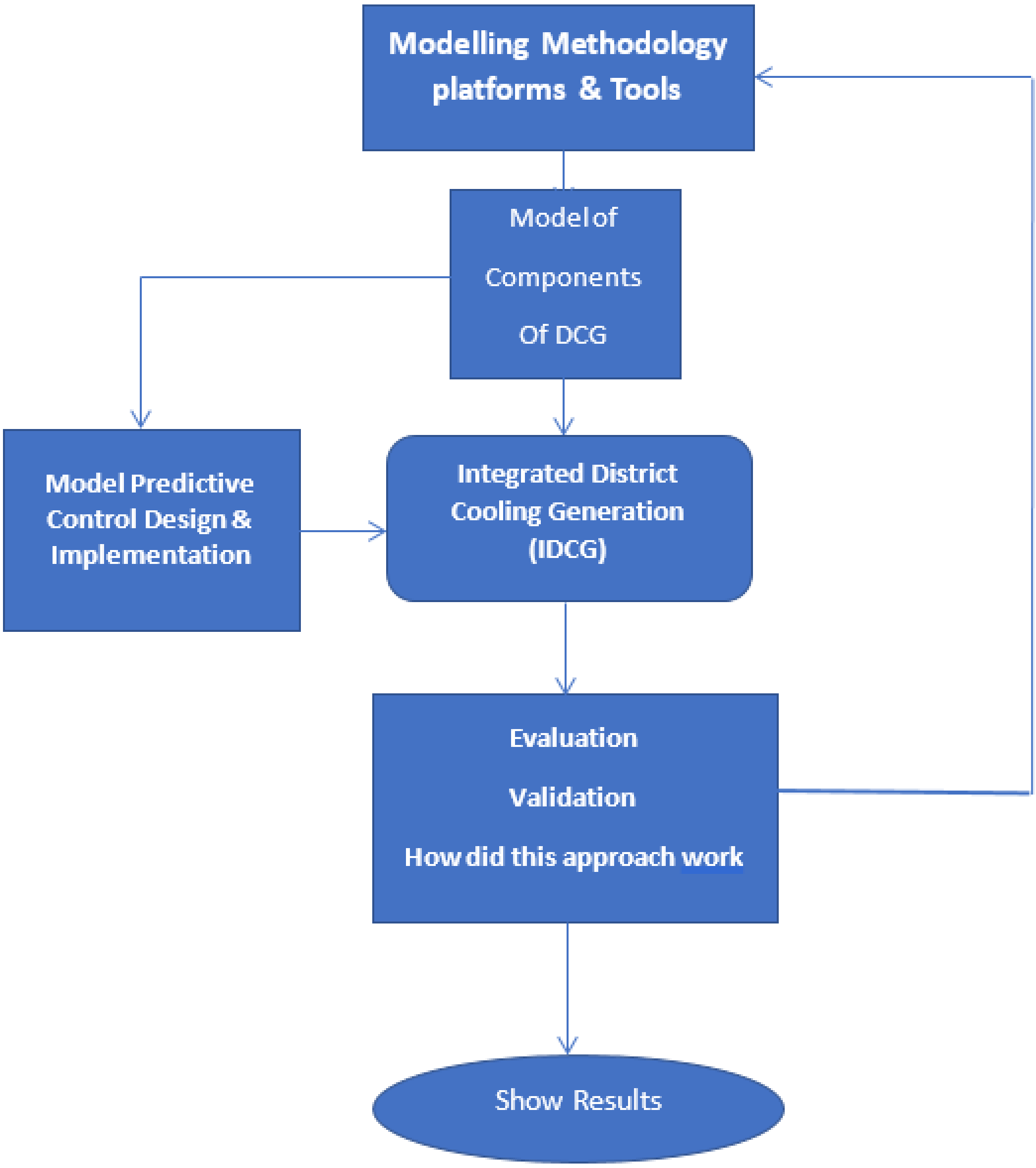


Figure 32: Integration algorithm for DCS generation

This thesis introduces several novel contributions to the field of DCG control, which are summarized as follows:

- The modelling is focused on DCG and how it can provide better solutions for MPC predictions. Therefore, this methodology can be used for any DCG modelling problem with MPC technologies.
- Prediction model of the MPC is based on developed Modelica models of DCG.
- An MPC problem with the constraints and limitation of the DCG in Basurto hospital is formulated.
- A methodology for the validation of results of model reduction and MPC algorithms is developed.
- MPC optimality and performance in DCG is theoretically analysed.
- Finally, the modelling and control methodologies are integrated into an algorithm that can be used in a generic way, providing a versatile and adaptable solution for a range of industrial applications.

To demonstrate the implementation of this methodology, the case study chapter for Basurto hospital building is presented in the next chapter.

4 Chapter 4: Case Study

This chapter is a description of the case study and consists of the background information of the DCG plant, measured data, the simulation methods, and tools. The description of the DCS test-site and generation plant are given below.

4.1 Description of Test Site

The test site is in Basurto Hospital in Bilbao, Spain (Figure 33).

Figure 33: Basurto Hospital (Retrieved from INDIGO project website [17]*)*

The hospital was constructed during the first decade of 20th century in the city of Bilbao and consists of 15 buildings now. Heating and cooling demand of the hospital is satisfied by a DHC installation connected to a trigeneration plant (the generation plant that feeds the DHC grid includes a Combined Heat and Power (CHP) based on a pair of gas engines). The CHP and DHCS were erected inside the hospital area in 2003 by VEOLIA and extended in 2011. This company currently operates the complete DHCS and the HVAC in the buildings. Nowadays, the trigeneration plant consists of two 2 MW natural gas internal combustion engines, two natural gas backup boilers, two absorption chillers and four conventional chillers. The gas engines generate electricity that is sold by VEOLIA to the Electric Grid. This way VEOLIA can offer cheaper electricity prices to the hospital than the usual market. Heat from the CHP is employed for DH supply as well as for feeding absorption chillers for DC supply. Apart from the heat coming from gas engines there are some gas boilers and conventional chillers for DH and DC supply, respectively. DH temperature level is 80ºC in supply and 65 ºC to 70 ºC in return while DC temperature level is 7ºC in supply and 10 ºC to 12ºC in return [109].

4.1.1 DCS Generation plant

The generation plant is located inside the hospital and includes chillers, storage, pumping and control.

4.1.1.1 Chilled water production

Figure 34 shows the layout of generation plant in Basurto Hospital. The chillers in the system are installed in parallel and are connected to supply and return circuits.

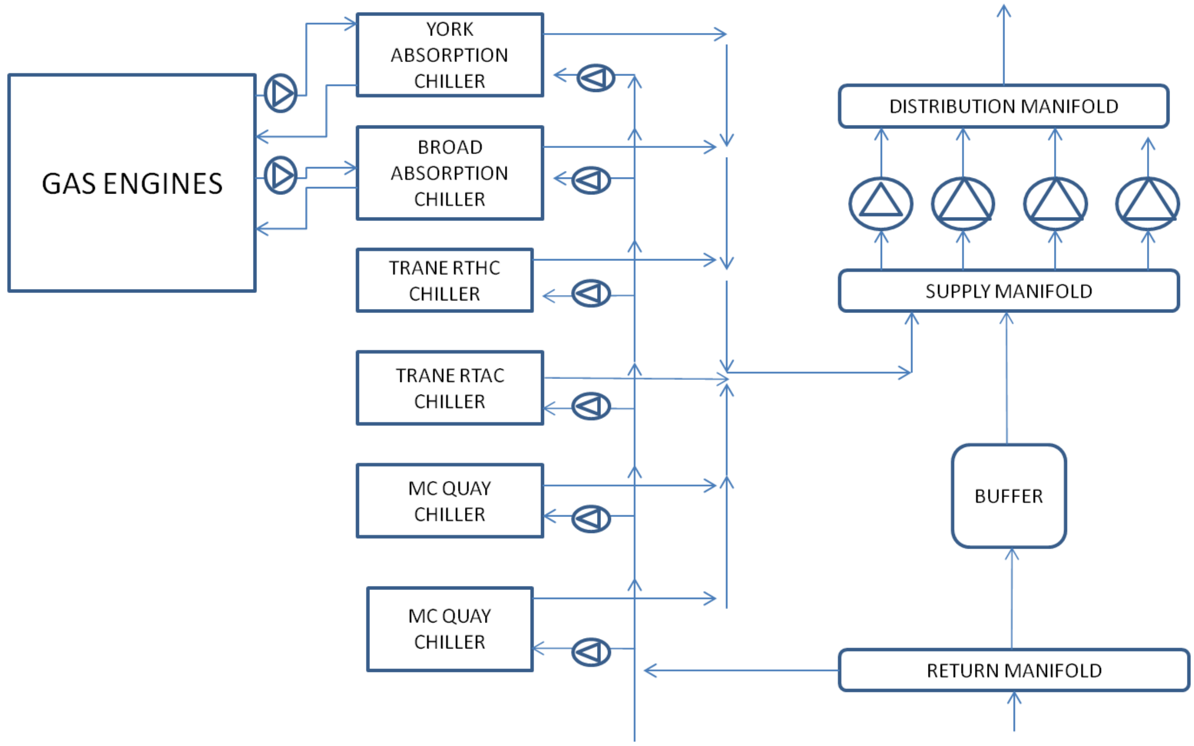


Figure 34. Generation plant simplified layout (Retrieved from INDIGO project [17])

Water-cooled chillers are connected to cooling towers from EVAPCO. Five cooling towers are connected to three chillers. BROAD absorption chiller is connected to a twin open cooling tower. YORK absorption chiller and TRANE conventional chiller (with heat rejection circuit in series) are connected to three closed cooling towers connected in parallel [109]. Table 7 is a summary of the characteristics of the six chillers.

Table 7. Characteristics of the chillers (Retrieved from INDIGO project [17])

Chiller type (Manufacturer)	Cooling capacity	Heat rejection
Single stage absorption chiller (YORK)	650 kW_t	Water-cooled
Single stage absorption chiller (BROAD)	1 MW_t	Water-cooled
Electrical chiller (TRANE)	1,5 MW_t	Water-cooled
Electrical chiller (TRANE)	730 kW_t	Air-cooled
2 x Electrical chiller (McQUAY)	974 kW_t	Air-cooled

Table 8 is a summary of the characteristics of the installed absorption chillers.

Table 8. Characteristics of the absorption chillers (Retrieved from INDIGO project [17])

Model of chiller	Hot water in/out	Chilled water in/out	Heat rejection water in/out	Cooling capacity	COP
BROAD BDH86X	39.7m^3/h 102.5ºC/72.5ºC	172 m^3/h 12ºC/7ºC	333 m^3/h 35ºC/29ºC	1000 kW	0.75
YORK YIA-HW-3B2	26 m^3/h 105ºC/65ºC	149 m^3/h 12ºC/7ºC	222.6 m^3/h 35ºC/29ºC	650 kW	0.69

Commonly maximum driven temperature during operation for these chillers in the installation is 105ºC. The rated conditions of the conventional chillers are shown in Table 9:

Table 9. Characteristics of the conventional chillers (Retrieved from INDIGO project [17])

Model of chiller	Chilled water in/out	Condenser inlet air temperature	Cooling capacity	COP or EER
McQuay AWS-XE-280.2	12ºC/7ºC	35ºC	974 kW	3.15
TRANE RTAC-200 (Low noise and High Eff. version)	12ºC/7ºC	35ºC	730 kW	2.85

MODEL	**CHILLED WATER IN/OUT**	**HEAT REJECTION WATER IN/OUT**	**COOLING CAPACITY**	**COP or EER**
TRANE RTHC-E3	12ºC/7ºC	29ºC/35ºC	1360-1560 kW	5.6-7

Regarding conventional chillers, there are four chillers that work with "R134a" as refrigerant. One of them is water-cooled and the other three are air-cooled (Air-cooled chillers are a safer option than water-cooled ones in terms of the possible health risks caused by Legionella bacteria.). Two air-cooled McQuay chillers were installed in 2011 while TRANE chillers are operating from the beginning [109].

Figure 35. McQuay conventional chiller at its location in the roof of the generation plant (Retrieved from INDIGO project [17])

Figure 36. TRANE air-cooled conventional chiller on the roof of the generation plant (Retrieved from INDIGO project [17]*)*

Figure 37. TRANE water-cooled conventional chiller in the generation plant (Retrieved from INDIGO project [17]*)*

The cold energy produced by each chiller is recorded by an energy meter installed in the corresponding cold-water circuit. Similarly, the total cold energy produced by the plant is also recorded in another energy meter connected to the main pipes of the district cooling network [109]. This recorded information can be used to measure the energy efficiency of the new algorithm compared to the conventional ones.

4.2 System structure, Monitoring, and Control

In terms of monitoring and control, the Basurto Hospital DC network is divided in Generation, water distribution, and Consumption (Buildings). The control systems of these two sites are different. The monitoring and control installed in the generation site is Supervisory Control And Data Acquisition (SCADA) modules programmed by Veolia and Genelek (local company with expertise in automation) with the architecture in Figure 38 [109]:

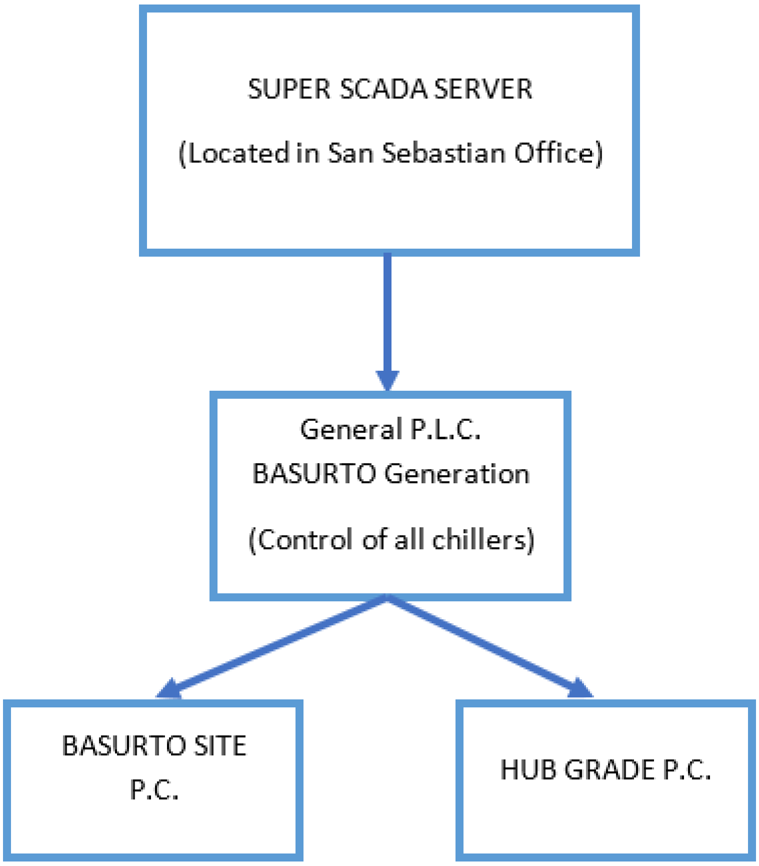


Figure 38: Genelek customized PLC topology (Retrieved from INDIGO project [17])

4.2.1.1 Chillers cascade control

Depending on cold demand from the hospital, the regulation will be starting machines in cascade so that the driving flow temperature never rises the established maximum temperature (ideally 12ºC for maximum performance).

The **control logic** is: Cold water theoretically is always sent to the hospital at 7 ºC and returns at 10/12 ºC, so the only variable is the flow that is sent to the hospital. When cold demand in the buildings rises, the regulation will increase the supply flow and inversely, when the demand goes down, it is a lower flow distribution. The six chillers work always between 7-12ºC. The number of running chillers must be such that the sum of the flows from the active chillers is greater than or equal to the flow rate that is sent to the hospital. Again, we can differentiate between two different ways of working:

Winter stage (December-April): As said before, Cogeneration engines are key in the cold-water production through the absorption chillers, so when they start, they fill up the hot storage tanks. In the meanwhile, in the first hours of the morning, if cold water is needed and absorption chillers are not ready, the McQuay electric chillers will supply water to the network. At 12:00, the BROAD absorption chiller will start, and the first McQuay will stop running. The first McQuay will run again if needed after the BROAD absorption chiller has started. Then, the second electric McQuay will start, followed by the air-cooled TRANE RTAC chiller. Neither TRANE RTHC nor YORK absorber chiller are programmed to work in winter stage.

Summer stage (May-November): In summer stage, as there is not much need for hot water for the hospital, hot water provided by co-generators can be fully used for the absorption chillers. So, at 7:00 the BROAD will start, followed by the YORK, followed by the two McQuay (2 x 1000 kW). If more cold water needed, this McQuay will start again, being the last one in use the TRANE RTAC due to be the oldest machine in place with the worse COP.

4.2.2 Available monitoring data in Generation

Regarding the generation plant, available data corresponds to every minute measurements of the next values since August 2016:

- Cold water produced in each chiller (energy meter)
- Hot water employed for feeding each absorption chiller (energy meter)
- Power use in each chiller
- Gas use of cogeneration engines

- Supply and return temperature of the cold-water circuit produced by each chiller
- Supply and return temperature of the driving hot water circuit of each absorption chiller
- Supply and return temperature of heat rejection water circuits (cooling towers)
- Water temperature in the supply and return manifolds
- Water pressure in supply and return of cooling ring (DC)
- Water temperatures at the top and the bottom of the buffer tank
- Ambient temperature (surroundings of the generation plant building)

4.3 Data collection from Basurto

This section is based on the data collection methodology that was explained in chapter 3. The project partner Veolia provides the connection to the Basurto hospital database through the following tool chain in Figure 39. The connection to the database was required to be set up every time when access was needed. In addition, the data was extracted in the form of arrays in a daily period for each signal.

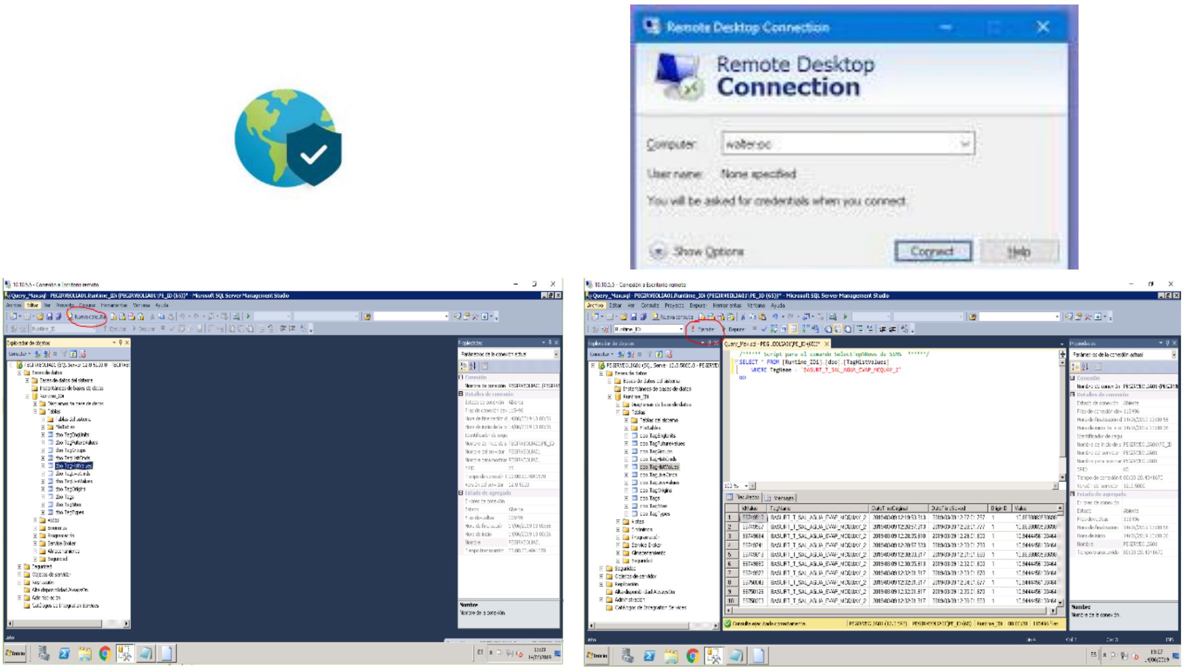


Figure 39: Toolchain for data collection

The data collection started in August 2017 and continued until August 2020 as new simulations were performed. The data was collected and recorded for whole day simulations.

The following steps were taken to collect the data for each of the inputs and outputs of DCG.

1. Connection to GlobalProtect64 software.
2. Connection to Remote Desktop in Veolia with Username & password dedicated to University of Galway using Windows Remote Desktop Connection
3. Open the Microsoft SQL server software & Open a 'New query'
4. SELECT * FROM [Runtime_IDi].[dbo].[TagHistValues]
   WHERE TagName = 'BASURT_T_SAL_AGUA_EVAP_MCQUAY_2'
   GO

The code to collect the data from the SQL management can be changed in a way to include certain time of the year or the desired sampling times.

The tag-names for each input and output are taken from Veolia datasheets mentioned in Table 10.

Table 10: Tag names for chiller inputs and outputs

Variable	Tag-Name in Basurto database
Electrical power use	BASURT_MBUS6_ENERGIA
Evaporator cold water outlet temperature	BASURT_T_SAL_AGUA_EVAP_MCQUAY_2
Evaporator cold water mass flow rate	BASURT_E2_CAUDAL_PRODUCC_FRIO
Cold water outlet temperature reference	BASURT_SPRem_T_SAL_AGUA_EV_MCQ2
Condenser cooling air inlet temperature	BASURT_T_EXTERIOR_FRIO_TT104
Evaporator cold water inlet temperature	BASURT_T_ENT_AGUA_EVAP_MCQUAY_2

Executing the SQL code for each tag name generates the values of the inputs/outputs based on the measurements of sensors (Figure 40).

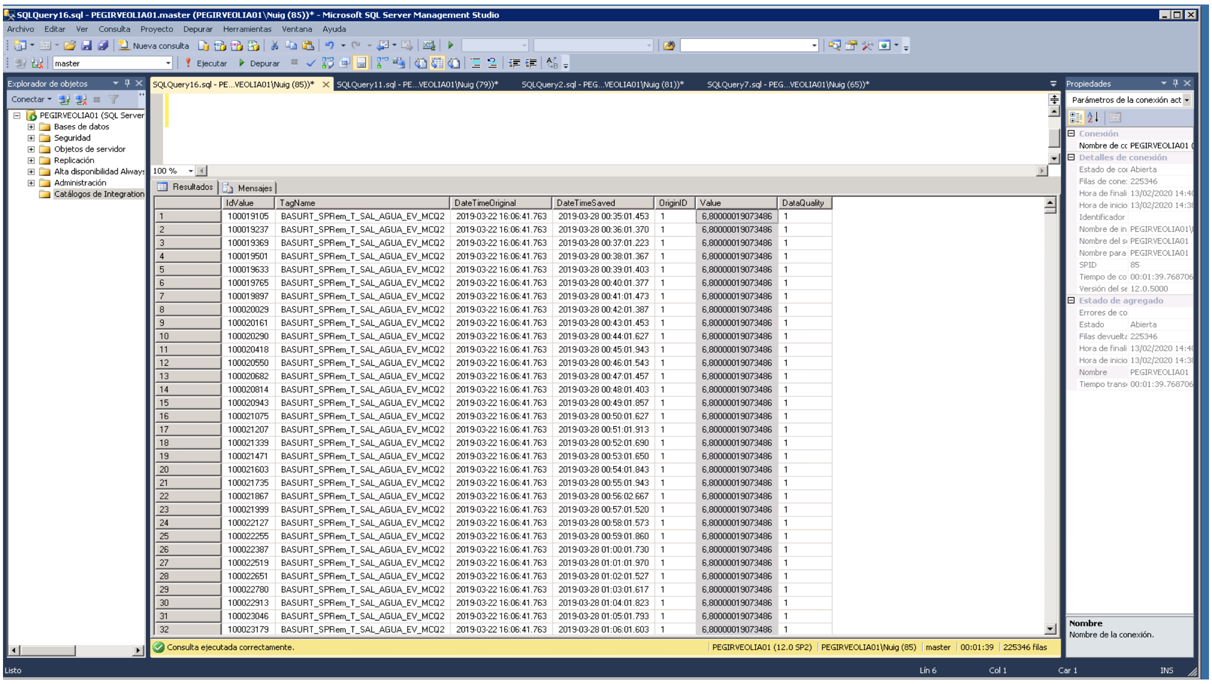


Figure 40: Basurto SQL database

4.4 MPC Implementation on DCG Case Study

MPC is an online optimisation algorithm that solves an optimisation problem at every single sampling time of the evolution of the system to optimize the cost function (e.g., minimize the error) based on the predictions from a model. A main advantage of MPC is that the physical constraints of the system can be considered directly in the problem formulation. In this subsection, the different parts of an MPC problem formulation in the context of the generation system of our case study are explained.

The following steps are taken to formulate the integrated modelling and control of DCG:

1. Define the decision variables including the optimisation variable.
2. Define the cost function and constraints.
3. Find out the type of optimisation problem (Linear, QP…)
4. Define MPC Horizon based on system dynamic and computational capacity.
5. Set the Solver and optimizer based on 3.
6. Let the solver run and obtain the solution.
7. Analyse the solution based on speed and value of cost function; Then against Basurto's physical data.

The chillers and cooling towers in the generation site of a DCS consume a considerable amount of energy to produce chilled water for the district. This case study aims at reducing this energy use by the application of the methodology explained in chapter 3. The two main goals are to minimize the energy use and to track the desired Temperature set-point based on the cooling water demand required from manager level.

After explaining the configuration of the existing equipment in the generation sites in the last section, the chillers and corresponding cooling tower to implement the MPCs for maximizing energy efficiency in the DCG are distinguished.

4.4.1 MPC Prediction Models

In this section, the case study results of the MPC of DCG are presented to validate the algorithms described in chapter 3.

4.4.1.1 Conventional Chiller Model

Figure 41 is the Modelica model available in EU H2020 INDIGO (2016-2020) project, DCOL Library [112]. EU H2020 INDIGO (2016-2020) – DCOL Library is Public and for each component, the following information is available:

- Detailed model calibration based on manufacturer's datasheet and data collected from Basurto Hospital
- Automated calibration code in Python
- Virtual Data generation (with random input with uniform distribution) along their valid range and with the frequency expected in the real system which characterises each component over the whole input ranges.

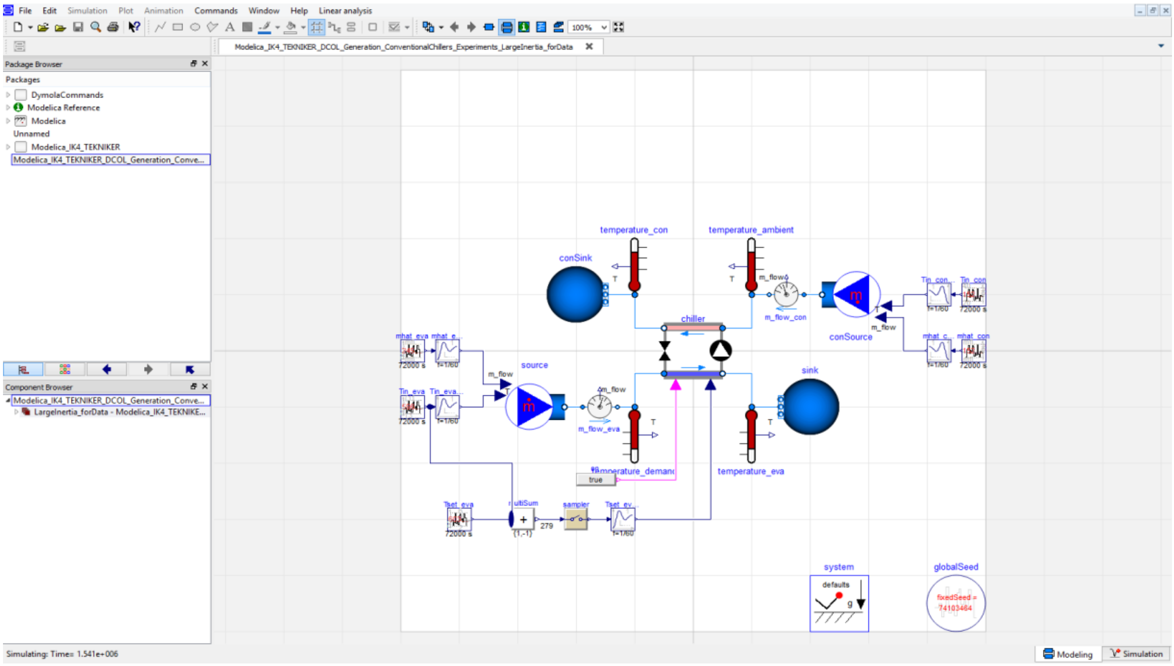


Figure 41: Graphical simulation of conventional chiller in Modelica

Inputs/Outputs/Disturbance of McQuay chiller:

- Chiller Inputs in control loop
    - Supply water temperature reference (T_{set}, K)
    - Evaporator inlet water mass flow rate ($\dot{m}, kg/s$)
- Chiller Disturbances
    - Condenser outlet water temperature (T_C, K)
    - Condenser inlet water temperature (T_E, K)
- Chiller outputs in control loop
    - Evaporator outlet water temperature (T_{out}, K)
    - Power use (P, W)

4.4.1.2 Cooling Tower Model

Figure 42 is the Modelica model of the cooling tower available in EU H2020 INDIGO (2016-2020) project, DCOL Library. The variables and parameters of the cooling tower of the case study are given below. The power use of the fan and the input and output of the cooling tower to the chiller's condenser are shown in Figure 43, Figure 44.

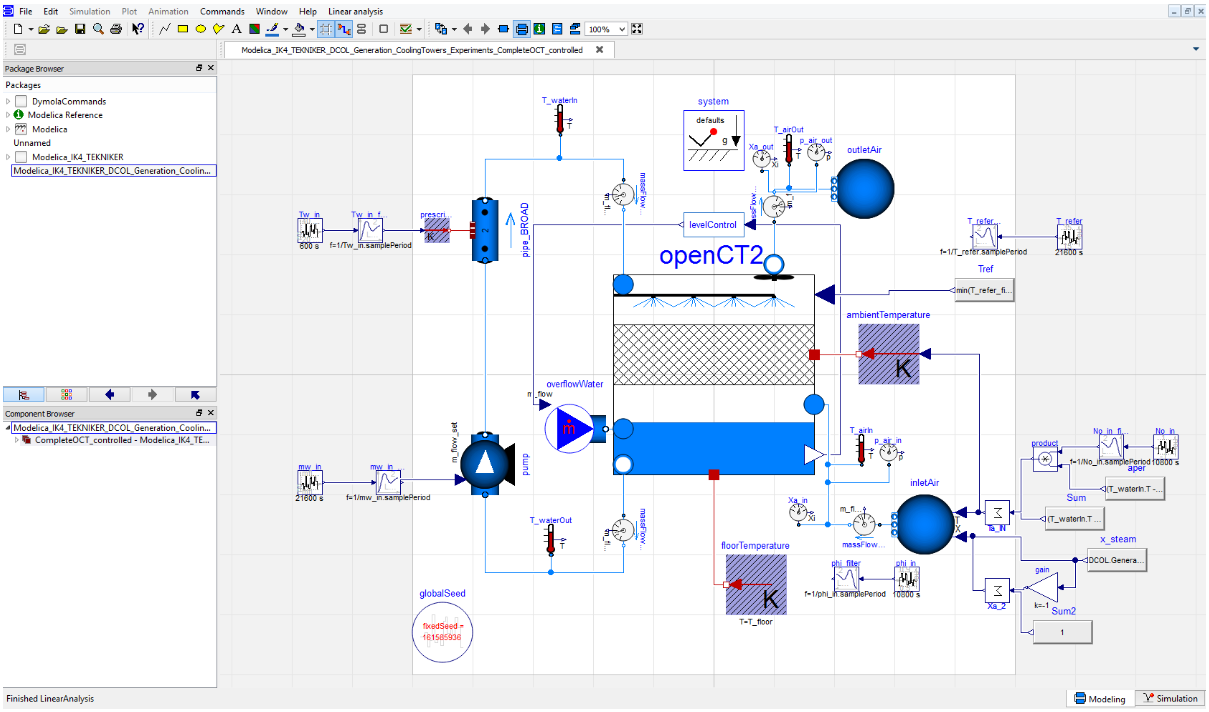


Figure 42: Graphical simulation of cooling tower in Modelica

Model structure: SSR LTI

Inputs/Outputs/Disturbance of the cooling tower

- Cooling tower inputs
  - Inlet flowrate into the condenser ($\dot{m}_c, kg/s$)
  - Set-point temperature of the inlet water from the chiller into the cooling tower (T_{ref_water}, K)
- Cooling tower disturbance
  - Temperature of the inlet water from heat rejection (T_{in_water}, K)
  - Relative Humidity (RH) of the inlet air to the fan (Weather data RH_{in_air}, kg^{-1})
  - Temperature of the inlet air to the fan (Weather data T_{in_air},K)
- Cooling tower outputs
  - Fan power use (P_{fan}, W)
  - Pump power use (P_{pump}, W)
  - Outlet temperature of the condenser (T_{oc}, K)

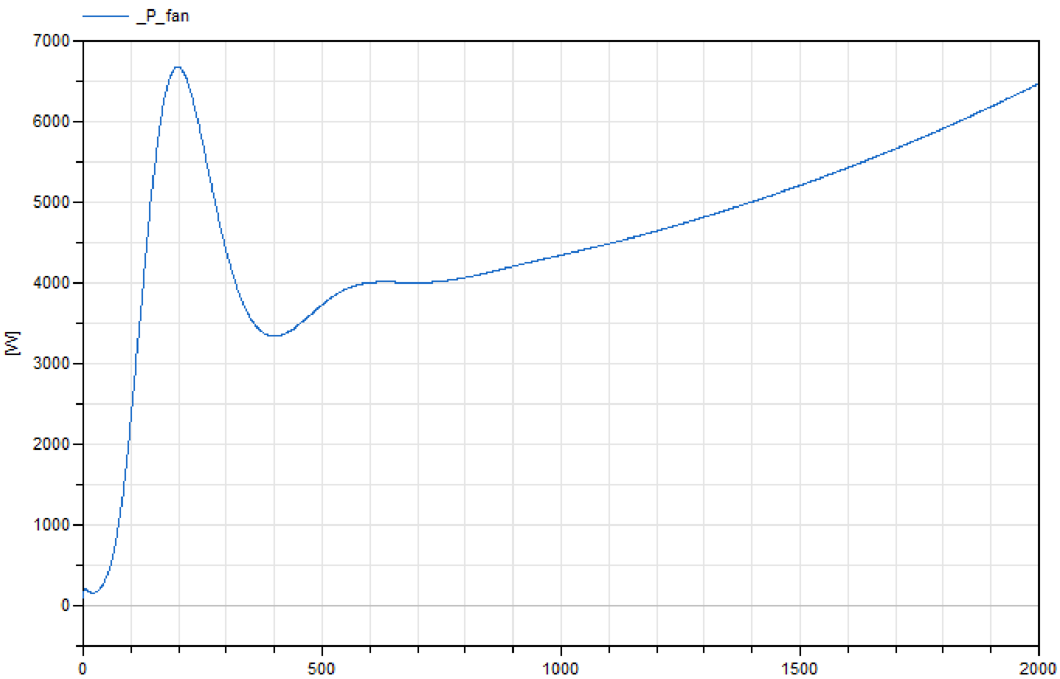


Figure 43: Power use of the cooling tower fan (W) in Time(s)

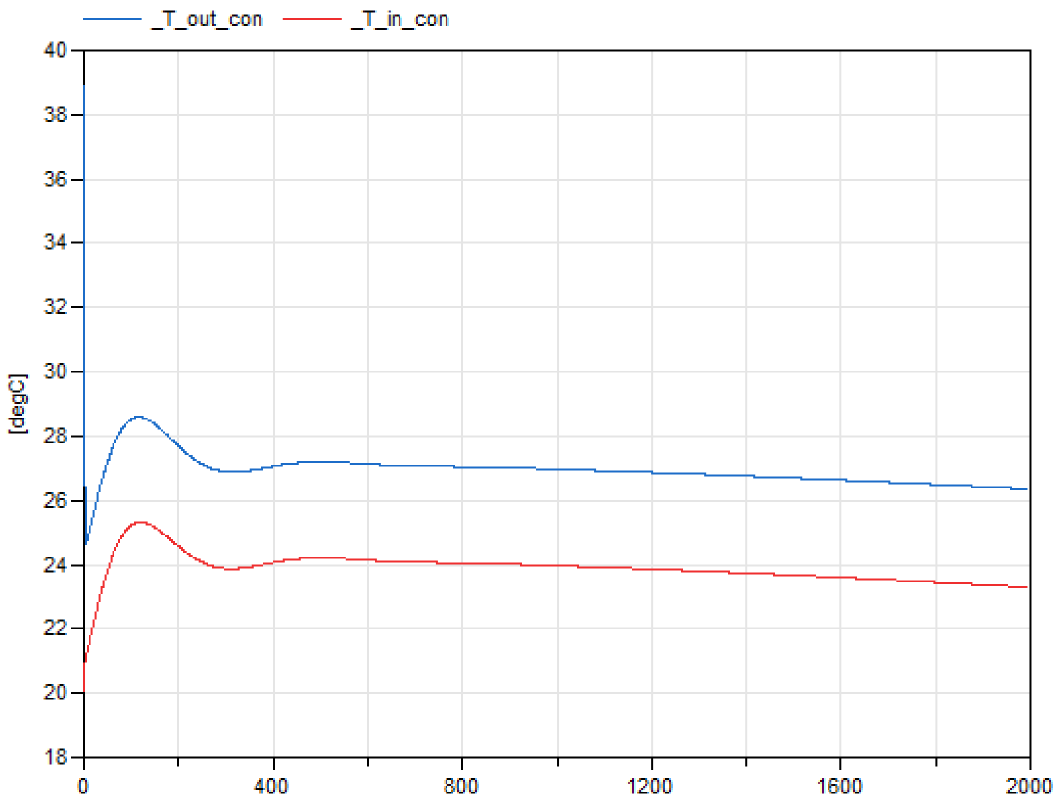


Figure 44: Input and output temperature of the condenser in heat rejection circuit of cooling tower (C) in Time(s)

The Modelica model is verified against the actual data. The prediction model is validated against the data available from the simulation of detailed Modelica models (Virtual data). This validated state space model is then used as prediction model in the MPC simulation [119].

Figure 45 summarizes the identification and validation process of the prediction model in a flowchart.

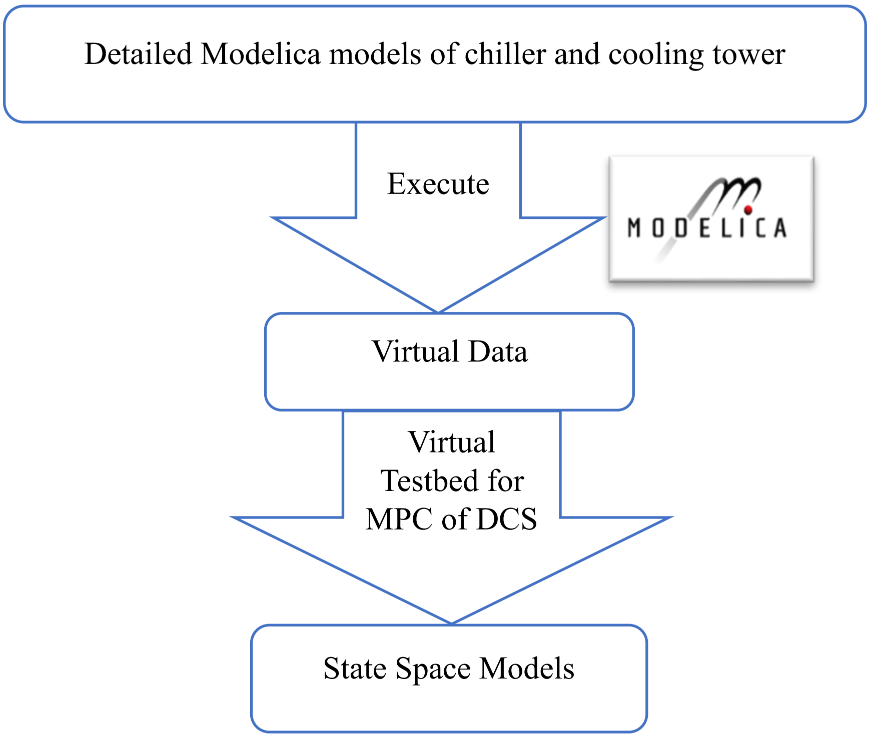


Figure 45: MPC prediction Model

4.4.2 MPC Optimisation Problem

4.4.2.1 Set-points

The setpoints of the variables of DCG are given from the SCADA. These setpoints are defined based on the steps in Figure 46. The manager decides on the value of the temperature at each sampling time (based on the cooling needs of the buildings) and communicates this value to the MPCs at the DCG component level at chillers. This given setpoint satisfies the thermal comfort requirements in the Surgical Block (BQ) building in Basurto Hospital based on the developments in INDIGO project [113].

Figure 46: Set-point requirements from the MPC at the Manager level

Remark 4.1: The predictive controllers are at the component level while the ranges of setpoints are defined from a higher level (the DCG manager) thus the ranges cannot be changed in this MPC implementation (hard constraint).

The power use is monitored at every sampling instant and is recorded in SQL database by Veolia.

4.4.2.2 Cost function

In the MPC formulation, the cost function includes the terms to minimize the energy use of the chiller and to maximize the thermal comfort (by tracking a desired setpoint temperature).

The two variables appearing in the cost function are:

- Electric power use of the chiller.
- Evaporator outlet water temperature setpoint.

The cost function is the sum of two quadratic terms of the difference of the variables and their desired value as in Equation 15:

$$cost = \alpha \sum (variable - desired\ value)^2$$

Equation 15: Cost function in error calculation format

We can regulate the terms of the objective function by weighting parameter α. The cost function is a quadratic function of the above two variables and thus leads to a Quadratic Programming (QP) problem.

4.4.2.3 Constraints

In generation systems, there are typically constraints on the rate of flow and the temperatures of the running fluids. These are **hard constraints** that need to be considered in designing the controllers, i.e., the system design implies these values, and we must consider them in implementing the optimisation problem. In this case study, we have two forms of constraints:

- The **rate of change** of a variable (e.g., water flow rate in the evaporator)
- The **minimum and maximum** of a variable (e.g., water flow rate in the evaporator)

Both these constraints are *linear equations* of the optimisation variables. In this case study, we have **upper and lower bounds** on the temperature values.

4.4.3 MPC Implementation Tools

We have so far implemented and formulated the DCG MPC problem. In this section, we present the tools and platforms that are used to solve the MPC problem in simulations.

4.4.3.1 Modelling the Optimisation Problem

Among various platforms available to solve optimisation and MPC problems, YALMIP modelling system is chosen. YALMIP is a modelling system that allows us to code the dynamics of a system and define the optimization problem, including cost and constraints, in a pre-specified format that is compatible with MATLAB. Furthermore, we can utilize different solvers within the YALMIP code by assigning the solver in the options of this platform.

- MATLAB R2020b – student License from the University of Galway and its updates.
- Optimisation Modelling System: YALMIP (https://yalmip.github.io/)

4.4.3.2 Solvers

The following QP solvers are used:

- Quadprog
- Fmincon
- Cplex
- MOSEK V8 (https://www.mosek.com/)
- SDPT3

Free academic Licenses are available for MOSEK, Cplex, and sdpt3. Quadprog and Fmincon can be called as functions inside a MATLAB code.

4.4.4 MPC Implementation Data

4.4.4.1 Verification of the McQuay chiller model

The detailed Modelica model has been verified against the actual data [112]. The data used in these simulations is the data that is derived from the simulations of the detailed Modelica models presented in [112]. This extracted data has its own sampling time of 1 second. The state space model of the chiller has also the sampling time of 1 second. The state-space model is validated by comparing it to the data from the detailed Modelica model simulation and calculating the corresponding errors using a virtual testbed.

The chiller's outlet temperature and power use are obtained from both the Modelica model (blue line), and the SS model (red line). The simulation of the models was performed for 24 h, and they led to similar graphs (Figure 47).

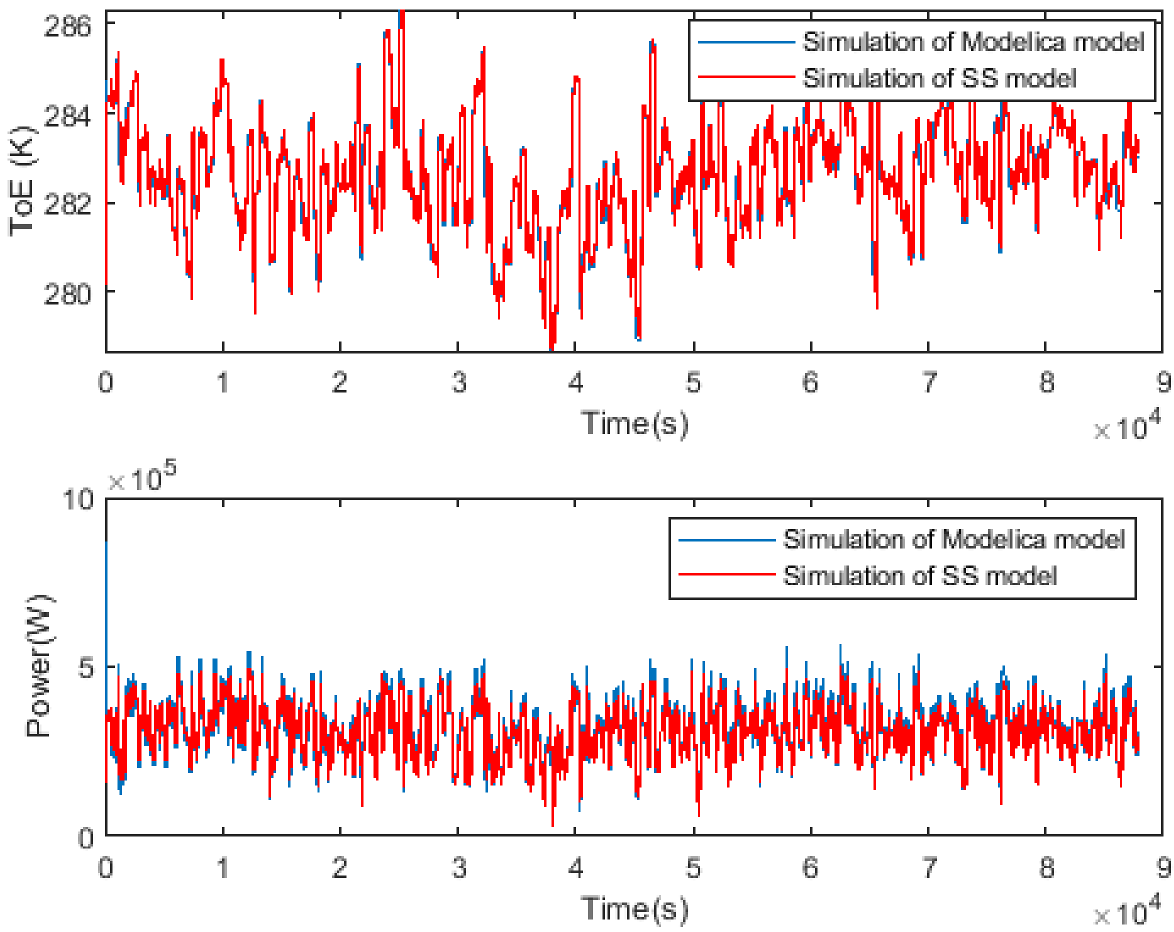


Figure 47: Results from the verification of the models for the *McQuay chiller*

The details of the validation of simulation models are given in article [112] as a joint work between EU H2020 INDIGO (2016-2020) partners.

As explained in the previous chapter, it is necessary to adjust the sampling time of the model, or the discretization step. The dynamics of the generation components are typically much slower and cannot be observed in 1 second. Therefore, the virtual data and the state-space models are resampled with a sampling time of 5 minutes. This allows for a longer MPC horizon of 15-30 minutes. With this validated data and state-space model (as the prediction model), we can now proceed with the MPC design.

4.5 Results of MPC of DCG

The described methodology is implemented in MATLAB using YALMIP with "Mosek" solver on a 64-bit windows 10 machine with intel core i5 at 1.6GHz, 8GB RAM, and 64-bit MATLAB, the computation times were about 1.2s YALMIP parsing time and 1.5s "Mosek" solving time.

1. The dynamics of the chiller are quite slow, so the state-space matrices are sampled with time steps of 5 minutes.
2. The resampled state-space model is introduced to the MPC to use as prediction model.
3. Define the weighting q, r for the outputs and inputs, respectively.

Table 11: Variable description for the chiller MPC problem

Variable	Description
Matrix $\boldsymbol{R}$	Output weighting matrix
Matrix $\boldsymbol{Q}$	Input weighting matrix
$\boldsymbol{T\_out\_eva\_max}$ $\boldsymbol{T\_out\_eva\_min}$	Bounds on outlet temperature of the chilled water
$\boldsymbol{P\_out\_max}$ $\boldsymbol{P\_out\_min}$	Bounds on consumed power
N	MPC horizon
Nsim	Simulation time
$\boldsymbol{m\_flow\_eva\_max}$ $\boldsymbol{m\_flow\_eva\_min}$	Bounds on evaporator water flow rate
$\boldsymbol{T\_set\_eva\_max}$ $\boldsymbol{T\_set\_eva\_min}$	Bounds on water setpoint temperature

Remark 4.2: (Comparison of Solvers) Quadprog was unable to solve the QP because it cannot deal with the big data involved in the implementation of the cost function, Cplex was slow and cannot continue to solve the problem after horizon 5 as the problem grows, ‘sdpt3’ ran into numerical issues in real-time predictions, but ‘MOSEK’ solved the optimisation problems of chiller MPC in real-time and for the full simulation horizon.

Figure 48 shows the chiller input signals in a one-day simulation. The inputs stay in the constraint bounds.

- Chiller Inputs
  - Cold water Temperature Reference (T_{set}, K)
  - Evaporator Inlet water mass flow rate ($\dot{m}, kg/s$)
- Chiller Disturbances
  - Ambient temperature (T_C, K)
  - Inlet temperature into the chiller from cooling tower (T_E, K)

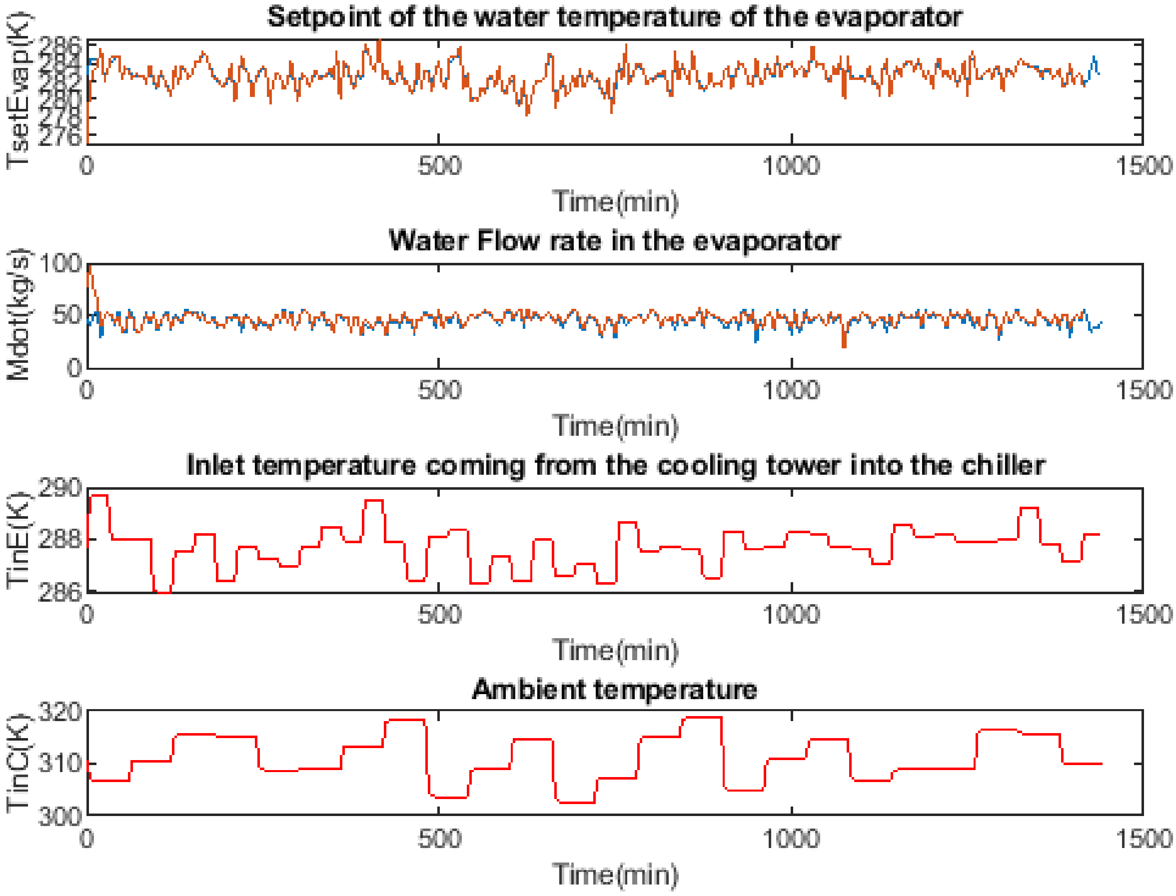


Figure 48: Inputs of chiller - MPC problem

Figure 49 is the demonstration of the outputs T_{out} and P in a one-day simulation time. The output temperature follows the setpoint, and the thermal comfort conditions are satisfied. In addition, the power is minimized.

Chiller Outputs

- Water Outlet temperature of the evaporator (T_{out}, K)
- Power use (P, W)

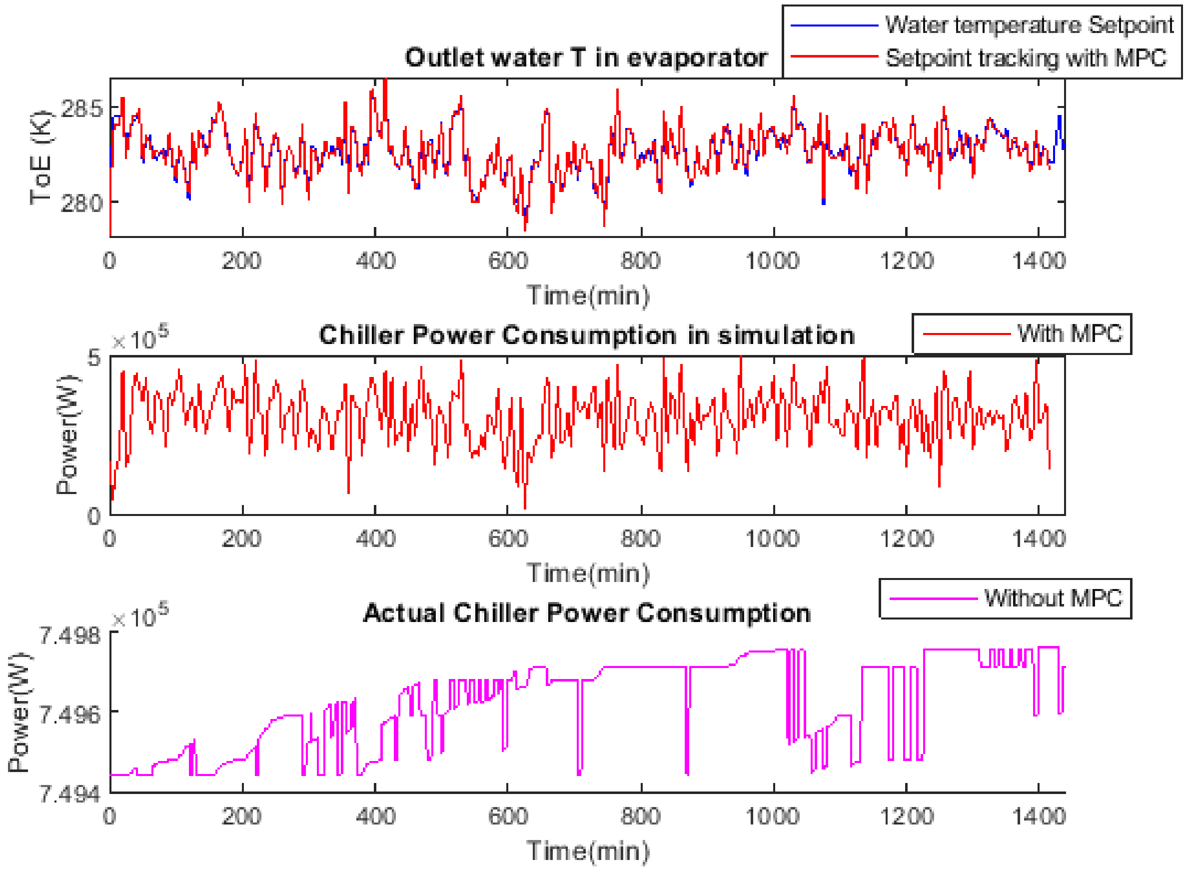


Figure 49: Outputs of chiller - MPC problem

The actual power consumption of the chiller (measured data) without MPC (with conventional PID) is shown on the bottom. The output water temperature (T_{out}) follows the setpoint water temperature (T_{set}). In addition, the power is minimized and stays in the bound.

Remark 4.3: Depending on the importance or preference of the temperature setpoint or energy efficiency goal, we could adjust the weighting factor r, q to emphasize one of the objective terms.

Result: The absolute error of the setpoint temperature tracking is calculated and shown in Figure 50 (below 0.1%).

Result: The power use is minimized by a factor of **1.5** compared to the actual chiller use without MPC (magnitude of 5×10^5 in the MPC compared to 7.5×10^5 in the actual measured data). In other words, the MPC achieved a theoretical 30% reduction in power consumption by calculating the sum of the absolute error between the power consumption in the MPC and measured data point by point during a one-day simulation and normalising it by the MPC absolute values.

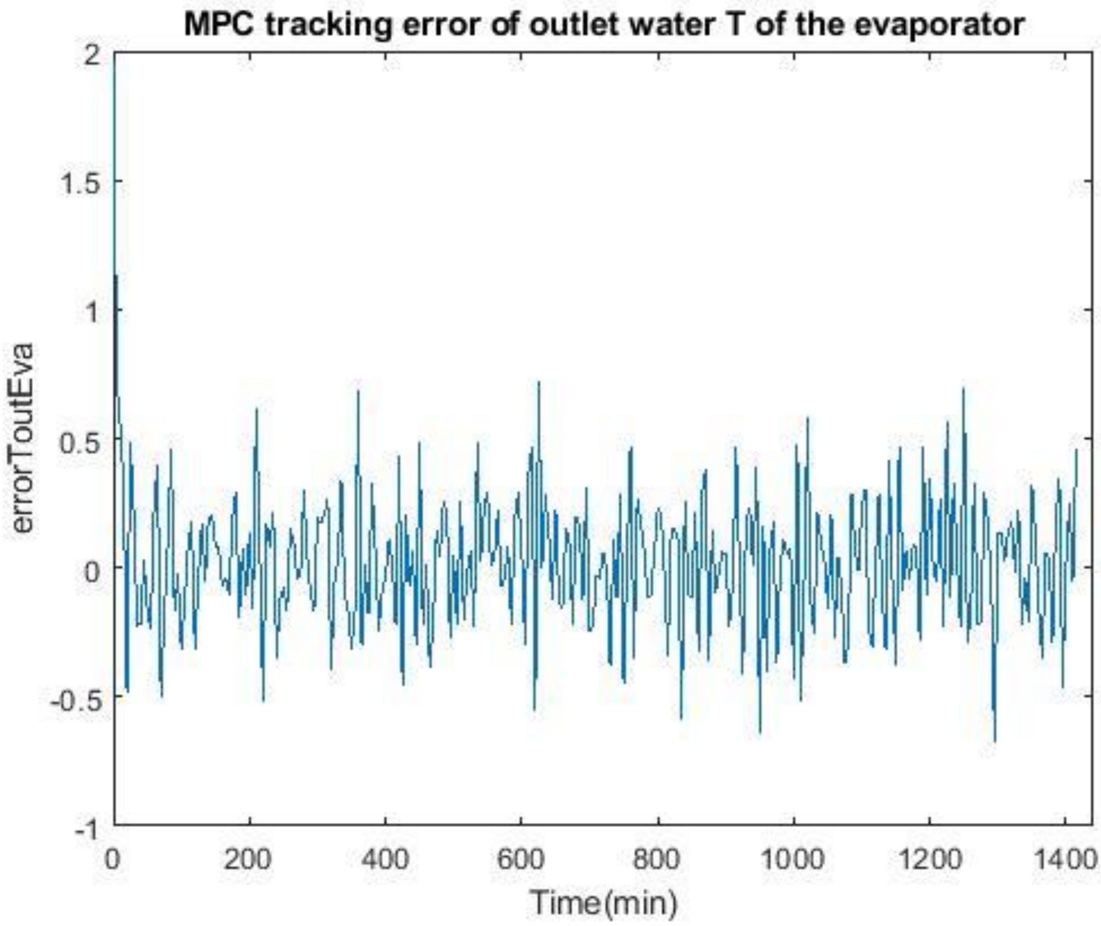


Figure 50: Tracking error of outlet water temperature of the evaporator by applying the MPC controller

Result: This MPC implementation is a generic code that can be used for other real-life applications of chillers with minor modifications depending on the objectives of the new problem. The tools used in this work are available online and they are open-source. These results are scalable and reusable in other applications of generation systems because the algorithm separates the model and optimisation problem structure, and the optimisation solving parts.

4.6 MPC Results Verification

This chapter presents the simulation results of a case study of a chiller to demonstrate the effectiveness of the proposed controller design methodology and mathematical solution. The following results are verified:

- The Hessian of Matrix F is positive semi-definite: F ≥ 0 (essential feature)

- The constraints are linear equality and inequality equations of the optimisation variables.
- The cost function is quadratic.
- The problem is thus Convex, quadratic and has an explicit solution.
- The Disturbances are measured and estimated.
    - The chiller measurement data is extracted from Basurto.
    - The data used for the prediction model is estimated from the simulation of the Modelica model.
- To solve the QP and store the explicit solution, a reasonable CPU power and sufficient memory are required. 'MOSEK' was used to solve the optimization problems of the generation MPC in real-time and for the full simulation horizon. Details regarding the specifications of the CPU, RAM, and solver can be found in the simulation remarks.

Remark 4.4: The fact that the problem is convex and has an explicit solution gives the option to use various solvers while the explicit solution makes it easier for the solver to perform a numerical analysis of the solution.

4.6.1 Key Performance Indicators

The Key Performance Indicators (KPI)s are:

- Error in the supplied temperature (To minimize error between the setpoint and the evaporator outlet water temperature)
- Power use (To achieve lower power use)

The goal is to evaluate the performance of the MPC controller based on the supplied cooling temperature and power use objectives at every iteration k =1…, N.

$$\text{Objective function}= \sum_{k=1}^{N-1}\{(T_{out}(k) - T_{set}(k))^2 + (P(k) - 0)^2\}$$

And to compare:

- Standard PI Controller (current installation)
- MPC

Remark 4.5:

- The already existing PID controls of the generation plant remain unchanged. The set-points of the cooling demand to be covered by each generation system are provided by the Management Controller, developed within work package 4 of INDIGO project [17].

- The manager decides on the value of the temperature at each sampling time and communicates this value with the MPCs at the component level.
- This is also a trial issue that we must use different QP solvers and look at the information of the optimisation problem when it is solved (speed of solving, hessian matrix of the optimisation, how much the cost function is minimized at each step of the optimisation).
- Weights of each term (supply temperature and consumed power) are set to one, i.e., model will emulate both outputs equally.
- The simulations are performed for 24 hours to include a full day study of the performance of the chiller.
- The mean absolute error of the temperature over the prediction horizon is below 1.5 degrees for at least 90% of the time.

5 Chapter 5: Conclusions and Future Work

In this chapter, the main conclusions of this thesis are presented. The results are discussed based on what was achieved in the methodology and case study of this thesis. The chapter concludes by providing recommendations for future work of this thesis based on the obtained results.

5.1 Conclusions

The literature review revealed the need for an integrated modelling and control approach to apply effective MPC algorithms on models of DCS. The methodology provided a detailed implementation of MPC for solving the optimal operation of the chillers and mathematical proof of the optimal solution.

Based on the studies performed in this thesis, the following conclusions can be drawn:

1. The literature review showed that a gap existed in applying MPC in practice and real-life applications of DCS. Although MPC is a developed technology among control theory researchers, MPC can be exploited to control the different components of DCS as well as its overall management. In this thesis, MPC was applied to the components of generation as chillers are the most energy consuming components of DCS.
2. The modelling was focused on DCG and how modelling techniques could provide better solutions for MPC prediction models. The prediction model is at the heart of the MPC implementation i.e., the prediction model affects the performance of the MPC controller. The modelling methodology was applied on a real-life application of DCG to provide prediction models. Therefore, the modelling methodology developed in this thesis can be used for any DCG modelling problem which will be used to apply MPC technologies.
3. An MPC problem with the constraints and limitation of the DCG in Basurto hospital is formulated. The data and the MPC testbed are extracted and simulated from a real-life application. The MPC algorithm presented in this thesis is a general formulation for control design of DCG components' controllers. The same MPC algorithm can be used for further applications of DCG with modifications based on the objective of the problem in other real-life applications.
4. It is important to see that the data-inefficiency scenario which occurred in this study was a significant barrier to achieve optimal operation of generation in terms of energy

use and thermal comfort through simulations. However, the theoretical analysis of the MPC optimal solution removed that barrier. The theoretical analysis ensured that the MPC solution exists and satisfies the constraints of the DCG.

5. Modelling and control methodologies are integrated into **IDCG methodology** (explained in section 3.8) that can be used in a generic way. The studies of this thesis were based on the fact that the modelling and control are inseparable and thus should be dealt with in an integrated way (resulted in IDCG). This paved the way for generating a prediction model that was used in the control algorithm. The IDCG methodology allows the user to take advantage of a full package of modelling and MPC technologies in the respective real-life application.
6. Regarding the tools used in the modelling and simulations, Modelica is an open-source language, and anyone can purchase a Modelica license online. YALMIP is also available on its website which is accessible by everyone. This means everyone can access the tools that are used for the modelling and simulations of this thesis. This makes the IDCG methodology scalable and reusable in other applications of DCG because the algorithms developed in this thesis are toolchains of the models developed in Modelica. The MPC problem is structured in MATLAB and the MPC optimisation is solved in YALMIP (Scalability and Reusability).
7. A theoretical 30% reduction in energy use of one chiller in the DCG component is a significant number that can be applied to any other DCG. This achievement is a steppingstone to replace the traditional PID controls with advanced yet computationally attainable MPC algorithms in the real-life DCG systems in the buildings and districts.

5.2 Future works

Suggestions for future work include the areas discussed below.

5.2.1 Robust MPC

Uncertainties in a DCS may arise from load calculations, layout of the network and the buildings in the model, and modelling and control methods. It is important to consider these uncertainties and ensure a robust performance for the DCS. Otherwise, these uncertainties can result in a prediction model which is not representative of the actual physical system of DCS and thus poor MPC controller performance. MPC has an inherent robustness in its algorithm because the MPC optimisation is solved at every sampling instant of the prediction model and provides a new actuation signal for the actuators at every sampling instant. However, the MPC optimisation does not distinguish where the source of uncertainty is or at which stage of IDCG the uncertainty has occurred (e.g., uncertainty in the measurements, prediction model, or load calculation). Robust MPC techniques ensure that any type of uncertainty arising at different stages of IDCG methodology can be dealt with individually. Thus, the future work of this thesis suggests including uncertainty in the data and/or prediction model (based on the source of uncertainty in DCS) and designing a robust MPC that deals with the uncertainties that may arise in DCS.

5.2.2 Adaptive MPC

The prediction model of the MPC of this thesis was based on developed Modelica models of DCG. This prediction model was developed and simulated once and then was used in the whole MPC prediction duration, i.e., the prediction model was fixed before the MPC implementation started. However, an advanced version of the prediction model can be an **adaptive prediction model** which reflects the dynamic changes of the model at every sampling instant. The adaptive prediction model evolves as the MPC algorithm is implemented and updates at every sampling instant. The advanced prediction model is that the prediction model would update at every simulation instant reflecting the disturbances that affect the system at any instant (not known beforehand), or the inherent uncertainties that arise in the physical system at any instant (not necessarily known beforehand). This idea is developed through MHE technique (or sometimes referred to as Adaptive MPC). The prediction model is estimated based on the measurements from the physical system as the MPC horizon moves further (Moving Horizon). The estimation of an adaptive prediction model at every sampling instant might require further measurements from the physical system.

5.2.3 Improving the Physical Setup

In the case study presented in this thesis at Basurto Hospital, the cooling tower had no actuation variable. This means that the setup of the chiller and cooling tower in the building was such that we could not intervene in the internal controls of the chiller's refrigeration cycle nor the control of the cooling tower's heat rejection circuit. In other cases, if the cooling tower can be actuated, it will create a Degree of Freedom (DOF) for the MPC controller. The extra DOF (the actuation potential) adds respective control variables in the MPC implementation and thus the physical setup allows an effective implementation of an adaptive MPC which was discussed in 5.2.2. Consequently, adding to the current actuation capacity (e.g., an actuated valve in the heat rejection circuit to actuate the inlet flowrate into the cooling tower condenser ($\dot{m}_c, kg/s$)) in the actual physical system of chillers and cooling towers can allow for adaptive MPC which is a suggestion for future work.

5.2.4 Application in a DCS

As a result of the suggestions made in 5.2.1, 5.2.2, 5.2.3, the future work would be to apply the developed Adaptive MPC to the components of a DCG in a full district. The analysis can be performed on a large-scale scenario where chillers and cooling towers have more DOF, the prediction model is adaptive and changing at a moving horizon, and the prediction model is estimated through the measurements provided from the actual physical model.

5.2.5 Flexibility services

Another idea for future work is the utilization of chiller power consumption optimisation results in providing flexibility services and participating in power price markets. This will involve evaluating the potential benefits of using chiller systems as a flexible resource to support the integration of renewable energy sources into the grid, as well as exploring the potential revenue streams available through participation in demand response programs and energy markets. Additionally, the effectiveness of different optimisation algorithms and control strategies could be examined to determine the most efficient and cost-effective approach for achieving the desired outcomes. Overall, the future work of this thesis aims to provide a deeper understanding of the role of chiller systems in the evolving energy landscape and identify new opportunities for maximizing their value and contribution to a more sustainable and resilient energy system.

6 References

[1] S. Werner, “International review of district heating and cooling,” *Energy*, pp. 1–15, 2017.

[2] R. Hitchin, C. Pout, and P. Riviere, “Assessing the market for air conditioning systems in European buildings,” *Energy Build.*, vol. 58, pp. 355–362, 2013.

[3] D. Olsthoorn, F. Haghighat, and P. A. Mirzaei, “Integration of storage and renewable energy into district heating systems: A review of modelling and optimization,” *Sol. Energy*, vol. 136, no. Supplement C, pp. 49–64, 2016.

[4] European Commission, “Energy efficiency: delivering the 20% target,” *Ann. Phys. (N. Y).*, vol. 54, no. November, p. 19, 2008.

[5] S. Skogestad and P. Mhaskar, “Introduction to the Special Issue on Energy Efficient Buildings,” *J. Process Control*, vol. 24, no. 6, pp. 701–702, 2014.

[6] Y. Yudong Ma, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, and P. Haves, “Model Predictive Control for the Operation of Building Cooling Systems,” in *American Control Conference*, 2010.

[7] B. Mayer, M. Killian, and M. Kozek, “A branch and bound approach for building cooling supply control with hybrid model predictive control,” *Energy Build.*, vol. 128, pp. 553–566, 2016.

[8] J. Okitsu, M. F. I. Khamis, N. Zakaria, K. Naono, and A. A. Haruna, “Toward an architecture for integrated gas district cooling with data center control to reduce {CO2} emission,” *Sustain. Comput. Informatics Syst.*, vol. 6, pp. 39–47, 2015.

[9] E. Fahlén, L. Trygg, and E. Ahlgren, “Potential CO2 reduction by increased integration of absorption cooling in a Swedish district energy system,” in *Proceedings of the 24th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, ECOS 2011*, 2011, pp. 3081–3094.

[10] J. L. M. Hensen and R. Lamberts, “Building Performance Simulation for Design and Operation.” Routledge, p. 1, 18-Jan-2011.

[11] A. Rong and R. Lahdelma, “Role of polygeneration in sustainable energy system development challenges and opportunities from optimization viewpoints,” *Renew.*

Sustain. Energy Rev., vol. 53, pp. 363–372, 2016.

[12] B. Rezaie and M. A. Rosen, "District heating and cooling: Review of technology and potential enhancements," *Appl. Energy*, vol. 93, pp. 2–10, 2012.

[13] C. Euroheat&Power, Cool Alliance (Logstor and Danfoss), "District cooling is 5-10 times more energy efficient than conventional cooling How district cooling works." 2016.

[14] S. Werner, "European space cooling demands," *Energy*, vol. 110, pp. 148–156, 2016.

[15] P. G. N. V. K. K.-R. A. P. L. A. O. Lars, "Best available technologies for the heat and cooling market in the European Union," 2012.

[16] European Parliament, "Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency," *Off. J. Eur. Union Dir.*, no. October, pp. 1–56, 2012.

[17] INDIGO partners, "INDIGO Project had received funding from European Union's Horizon 2020 research and innovation programme, under grant agreement n 696098."

[18] S. Ben Amer-Allam, M. Münster, and S. Petrović, "Scenarios for sustainable heat supply and heat savings in municipalities - The case of Helsingør, Denmark," *Energy*, p. , 2017.

[19] S. Huang, "Model based Technologies for Enhancing Building Operation," 2016.

[20] J. Drgoňa *et al.*, "All you need to know about model predictive control for buildings," *Annu. Rev. Control*, vol. 50, pp. 190–232, 2020.

[21] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," vol. 14, pp. 207–222, 2003.

[22] M. Brum, P. Erickson, B. Jenkins, and K. Kornbluth, "A comparative study of district and individual energy systems providing electrical-based heating, cooling, and domestic hot water to a low-energy use residential community," *Energy Build.*, vol. 92, pp. 306–312, 2015.

[23] T. T. Chow, K. F. Fong, A. L. S. Chan, R. Yau, W. H. Au, and V. Cheng, "Energy modelling of district cooling system for new urban development," *Energy Build.*, vol.

36, no. 11, pp. 1153–1162, 2004.

[24] W. Gang, G. Augenbroe, S. Wang, C. Fan, and F. Xiao, "An uncertainty-based design optimization method for district cooling systems," *Energy*, vol. 102, pp. 516–527, 2016.

[25] T. M. Lawrence, R. T. Watson, M.-C. Boudreau, and J. Mohammadpour, "Data Flow Requirements for Integrating Smart Buildings and a Smart Grid through Model Predictive Control," *Procedia Eng.*, vol. 180, pp. 1402–1412, 2017.

[26] J. Söderman, "Optimisation of structure and operation of district cooling networks in urban regions," *Appl. Therm. Eng.*, vol. 27, no. 16, pp. 2665–2676, 2007.

[27] T. Nagota, Y. Shimoda, and M. Mizuno, "Verification of the energy-saving effect of the district heating and cooling system—Simulation of an electric-driven heat pump system," *Energy Build.*, vol. 40, no. 5, pp. 732–741, 2008.

[28] S. Werner, "International review of district heating and cooling," *Energy*, vol. 137, pp. 617–631, 2017.

[29] J. Palm and S. Gustafsson, "Barriers to and enablers of district cooling expansion in Sweden," *J. Clean. Prod.*, vol. 172, pp. 39–45, 2018.

[30] A. L. S. Chan, T. T. Chow, S. K. F. Fong, and J. Z. Lin, "Performance evaluation of district cooling plant with ice storage," *Energy*, vol. 31, no. 14, pp. 2414–2426, 2006.

[31] Y. Shimoda, T. Nagota, N. Isayama, and M. Mizuno, "Verification of energy efficiency of district heating and cooling system by simulation considering design and operation parameters," *Build. Environ.*, vol. 43, no. 4, pp. 569–577, 2008.

[32] W. Gang, S. Wang, F. Xiao, and D. Gao, "Performance Assessment of District Cooling System Coupled with Different Energy Technologies in Subtropical Area," in *Energy Procedia*, 2015, vol. 75, pp. 1235–1241.

[33] M. Sakawa, S. Ushiro, K. Kato, and K. Ohtsuka, "Cooling load prediction in a district heating and cooling system through simplified robust filter and multi-layered neural network," in *Systems, Man, and Cybernetics, 1999. IEEE SMC '99 Conference Proceedings. 1999 IEEE International Conference on*, 1999, vol. 3, pp. 995–1000 vol.3.

[34] A. Carotenuto, R. D. Figaj, and L. Vanoli, "A novel solar-geothermal district heating, cooling and domestic hot water system: Dynamic simulation and energy-economic analysis," *Energy*, 2017.

[35] C. Damien, N. Cynthia, B. Guillaume, S. Pascal, and M. Dominique, "Dynamic Modelling of a District Cooling Network With Modelica," *14th Int. Conf. IBPSA - Build. Simul. 2015, BS 2015, Conf. Proc.*, pp. 1569–1576, 2015.

[36] A. Preisler *et al.*, "Development of a Technology Roadmap for Solar Thermal Cooling in Austria," *Energy Procedia*, vol. 30, pp. 1422–1431, 2012.

[37] E. M. Moe, "Building performance with district cooling," *ASHRAE J.*, vol. 47, no. 7, pp. 46–53, 2005.

[38] W. Gang, S. Wang, F. Xiao, and D. Gao, "District cooling systems: Technology integration, system optimization, challenges and opportunities for applications," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 253–264, 2016.

[39] J. Gao, J. Kang, C. Zhang, and W. Gang, "Energy performance and operation characteristics of distributed energy systems with district cooling systems in subtropical areas under different control strategies," *Energy*, vol. 153, pp. 849–860, 2018.

[40] B. Skagestad and P. Mildenstein, *District Heating and Cooling Connection Handbook - Programme of Research, Development and Demonstration on District Heating and Cooling*. 2002.

[41] Z. X. Jing, X. S. Jiang, Q. H. Wu, W. H. Tang, and B. Hua, "Modelling and optimal operation of a small-scale integrated energy based district heating and cooling system," *Energy*, vol. 73, pp. 399–415, 2014.

[42] J. I. Levenhagen and D. H. Spethmann, *HVAC controls and systems*. McGraw-Hill, 1993.

[43] M. Murai, Y. Sakamoto, and T. Shinozaki, "An optimizing control for district heating and cooling plant," in *Control Applications, 1999. Proceedings of the 1999 IEEE International Conference on*, 1999, vol. 1, pp. 600–604 vol. 1.

[44] M. B. Kane and J. P. Lynch, "An agent-based model-predictive controller for chilled water plants using wireless sensor and actuator networks," *2012 American Control*

Conference (ACC). pp. 1192–1198, 2012.

[45] B. Huberman and S. H. Clearwater, “A Multi-Agent System for Controlling and Building Environments,” *Proc. First Int. Conf. Multiagent Syst.*, pp. 171–176, 1995.

[46] Z. Peng, S. Suryanarayanan, and M. G. Simoes, “An Energy Management System for Building Structures Using a Multi-Agent Decision-Making Control Methodology,” *Ind. Appl. IEEE Trans.*, vol. 49, no. 1, pp. 322–330, 2013.

[47] T. T. Chow, A. L. S. Chan, and C. L. Song, “Building-mix optimization in district cooling system implementation,” *Appl. Energy*, vol. 77, no. 1, pp. 1–13, 2004.

[48] X.-Q. . b Jiang, W.-D. . Long, and M. . Li, “Hourly cooling load analysis and prediction in a district cooling system,” *Zhongnan Daxue Xuebao (Ziran Kexue Ban)/Journal Cent. South Univ. (Science Technol.*, vol. 41, no. 1, pp. 357–363, 2010.

[49] R. Khir and M. Haouari, “Optimization models for a single-plant District Cooling System,” *Eur. J. Oper. Res.*, vol. 247, no. 2, pp. 648–658, 2015.

[50] G.-Q. Zhang, Y.-Z. Xu, J. Han, T. Liu, and H.-P. Wu, “Research on optimal economic temperature difference between the chilled water supply and return model of a district-cooling system,” *Hunan Daxue Xuebao/Journal Hunan Univ. Nat. Sci.*, vol. 42, no. 9, pp. 128–133, 2015.

[51] G. Wang, B. Zheng, and M. Liu, “Impacts on building return water temperature in district cooling systems,” in *International Solar Energy Conference*, 2006, vol. 3, pp. 1415–1422.

[52] Z. Xuan *et al.*, “New cooling regulation technology of secondary cooling station in DCS,” *Energy Build.*, vol. 40, no. 7, pp. 1171–1175, 2008.

[53] M. Diehl, “Script for Numerical Optimization Course,” 2012.

[54] M. Sakawa, K. Kato, and S. Ushiro, “Operation planning of district heating and cooling plants using genetic algorithms for mined 0-1 linear programming,” in *Industrial Electronics Society, 2000. IECON 2000. 26th Annual Confjerence of the IEEE*, 2000, vol. 4, pp. 2915–2920 vol.4.

[55] Z. Xuan, Y. Junwei, Z. Dongsheng, and L. Liequan, “Triple Reverse Cool Adjustment and Control Technology with DCS,” in *2007 Chinese Control Conference*, 2007, pp.

418–421.

[56] X. Wei, G. Xu, and A. Kusiak, “Modeling and optimization of a chiller plant,” *Energy*, vol. 73, pp. 898–907, 2014.

[57] X. Li, Y. Li, J. E. Seem, and P. Li, “Extremum seeking control of cooling tower for self-optimizing efficient operation of chilled water systems,” *2012 American Control Conference (ACC)*. pp. 3396–3401, 2012.

[58] Z. May, N. M. Nor, K. Jusoff, and U. T. Petronas, “Optimal Operation of Chiller System Using Fuzzy Control,” *AIKED’11 Proc. 10th WSEAS Int. Conf. Artif. Intell. Knowl. Eng. data bases*, pp. 109–115, 2011.

[59] S. J. Cox, D. Kim, H. Cho, and P. Mago, “Real time optimal control of district cooling system with thermal energy storage using neural networks,” *Appl. Energy*, vol. 238, pp. 466–480, 2019.

[60] Z. Hou and Z. Wang, “From model-based control to data-driven control : Survey , classification and perspective,” *Inf. Sci. (Ny).*, vol. 235, pp. 3–35, 2013.

[61] P. Bacher and H. Madsen, “Identifying suitable models for the heat dynamics of buildings,” *Energy Build.*, vol. 43, no. 7, pp. 1511–1522, 2011.

[62] D. Coakley, “Calibration of Detailed Building Energy Simulation Models to Measured Data using Uncertainty Analysis- PhD thesis,” p. 299, 2014.

[63] M. Wetter, “Simulation Model: Air-to-Air Plate Heat Exchanger, LBNL-42354,” *Convergence*, no. January, pp. 1–12, 1998.

[64] M. Wetter, “Simulation Model Finned Water-to-Air Coil without Condensation,” pp. 1–19, 1998.

[65] J. L. Jean-Pascal Bourdouxhe, Marc Grodent, *Reference Guide for Dynamic Models of HVAC Equipment*. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Incorporated, 1998.

[66] B. Tashtoush, M. Molhim, and M. Al-Rousan, “Dynamic model of an HVAC system for control analysis,” *Energy*, vol. 30, no. 10, pp. 1729–1745, 2005.

[67] T. Oppelt, T. Urbaneck, and B. Platzer, “District cooling networks: Comparison of models for calculating heat flow through walls of buried parallel pipes,” *Euroheat*

Power (English Ed., vol. 10, no. 2, pp. 26–31, 2013.

[68] D. Eriksson and B. Sunden, “Heat and mass transfer in polyurethane insulated district cooling and heating pipes,” *J. Therm. Envel. Build. Sci.*, vol. 22, pp. 49–71, 1998.

[69] J.-P. . Liu, Y.-G. . Du, and Z.-Q. . Chen, “Optimized design of the chilled water-conveying pipeline in the district cooling system,” *Huanan Ligong Daxue Xuebao/Journal South China Univ. Technol. (Natural Sci.*, vol. 32, no. 10, pp. 28-31+35, 2004.

[70] X. Feng and W. Long, “Optimal design of pipe network of district cooling system based on genetic algorithm,” in *2010 Sixth International Conference on Natural Computation*, 2010, vol. 5, pp. 2415–2418.

[71] H. Magori, S. Kurihara, Z. Yicheng, and R. Yokoyama, “Development of an extended DP optimization method applied to a district heating and cooling energy supply system,” in *Power Engineering Society Winter Meeting, 2000. IEEE*, 2000, vol. 2, pp. 981–986 vol.2.

[72] G. Schweiger, P.-O. Larsson, F. Magnusson, P. Lauenburg, and S. Velut, “District heating and cooling systems – Framework for Modelica-based simulation and dynamic optimization,” *Energy*, 2017.

[73] D. B. Crawley, C. O. Pedersen, L. K. Lawrie, and F. C. Winkelmann, “EnergyPlus: Energy Simulation Program,” *ASHRAE J.*, vol. 42, pp. 49–56, 2000.

[74] S. A. Klein, W. A. Beckman, and J. A. Duffie, “TRNSYS—a transient simulation program,” *ASHRAE Trans.*, vol. 82, 1976.

[75] T. M. Association, “{T}he {M}odelica {A}ssociation {H}ome {P}age,” 2012.

[76] T. S. Nouidui and M. Wetter, “Tool coupling for the design and operation of building energy and con- trol systems based on the Functional Mock-up Interface standard Co-simulation,” pp. 311–320, 2014.

[77] J. Wetter, M., Treeck, C. Van & Hensen, “EBC Annex 60 New generation computational tools for building and community energy systems,” 2013.

[78] M. Wetter, M. Bonvini, T. S. Nouidui, W. Tian, and W. Zuo, “MODELICA BUILDINGS LIBRARY 2 . 0 Lawrence Berkeley National Laboratory , Berkeley ,

CA University of Miami , Coral Gables FL," *Build. Simul. Conf.*, pp. 387–394, 2015.

[79] S. Wang, "Dynamic Simulation of a Building Central Chilling System and Evaluation of EMCS On-Line Control Strategies," *Build. Environ.*, vol. 33, no. 1, pp. 1–20, 1998.

[80] D. Coakley, P. Raftery, and M. Keane, "A review of methods to match building energy simulation models to measured data," *Renew. Sustain. Energy Rev.*, vol. 37, pp. 123–141, 2014.

[81] J. B. Rawlings and D. Q. Mayne, *Model Predictive Control: Theory and Design*. Nob Hill Pub., 2009.

[82] Y. Ma, F. Borrelli, and B. Hencey, "Model predictive control for the operation of building cooling systems," *Control Syst. …*, pp. 1–8, 2012.

[83] M. Vande Cavey, R. De Coninck, and L. Helsen, "Setting up a framework for model predictive control with moving horizon state estimation using JModelica," *10th Int. Model. Conf.*, no. September 2015, pp. 1295–1303, 2014.

[84] S. Wang and X. Xu, "Simplified building model for transient thermal performance estimation using GA-based parameter identification," *Int. J. Therm. Sci.*, vol. 45, no. 4, pp. 419–432, 2006.

[85] O. Pol and A. Preisler, "Optimized load profiles for a district cooling network supported by absorption chillers using thermally activated building component systems (TABS)," in *PROCEEDINGS OF THE 5TH INTERNATIONAL SYMPOSIUM ON HEATING, VENTILATING AND AIR CONDITIONING, VOLS I AND II*, 2007, pp. 29–36.

[86] J. Kang, S. Wang, and C. Yan, "A new distributed energy system configuration for cooling dominated districts and the performance assessment based on real site measurements," *Renew. Energy*, vol. 131, pp. 390–403, 2019.

[87] J. A. Romero, J. Navarro-Esbr??, and J. M. Belman-Flores, "A simplified black-box model oriented to chilled water temperature control in a variable speed vapour compression system," *Appl. Therm. Eng.*, vol. 31, no. 2–3, pp. 329–335, 2011.

[88] B. Mu, Y. Li, T. I. Salsbury, and J. M. House, "Optimization and sequencing of chilled-water plant based on extremum seeking control," *2016 American Control Conference (ACC)*. pp. 2373–2378, 2016.

[89] L. Yao and K. Jaiteh, “Multi-objective control of central air conditioning system,” *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. pp. 1–6, 2017.

[90] T. Li, Q. Ren, and H. Zhao, “Research on Optimal Control of Cooling Water System in Central Air Conditioning System,” *2013 Fourth International Conference on Intelligent Systems Design and Engineering Applications*. pp. 511–514, 2013.

[91] K. Deng *et al.*, “Model Predictive Control of Central Chiller Plant With Thermal Energy Storage Via Dynamic Programming and Mixed-Integer Linear Programming,” *IEEE Transactions on Automation Science and Engineering*, vol. 12, no. 2. pp. 565–579, 2015.

[92] P. Schalbart, D. Leducq, and G. Alvarez, “Ice-cream storage energy efficiency with model predictive control of a refrigeration system coupled to a {PCM} tank,” *Int. J. Refrig.*, vol. 52, pp. 140–150, 2015.

[93] S. Engell and I. Harjunkoski, “Optimal operation: Scheduling, advanced control and their integration,” *Comput. Chem. Eng.*, vol. 47, pp. 121–133, 2012.

[94] U. Bau, A.-L. Braatz, F. Lanzerath, M. Herty, and A. Bardow, “Control of adsorption chillers by a gradient descent method for optimal cycle time allocation,” *Int. J. Refrig.*, vol. 56, pp. 52–64, 2015.

[95] S. Antonov and L. Helsen, “Robustness analysis of a hybrid ground coupled heat pump system with model predictive control,” *J. Process Control*, vol. 47, pp. 191–200, 2016.

[96] B. G. V. Lara, L. M. C. Molina, and J. P. M. Yanes, “Modeling and identification of the cooling dynamics of a tropical island hotel,” *Energy Build.*, vol. 92, pp. 19–28, 2015.

[97] J. (Dove) Feng, F. Chuang, F. Borrelli, and F. Bauman, “Model predictive control of radiant slab systems with evaporative cooling sources,” *Energy Build.*, vol. 87, pp. 199–210, 2015.

[98] K. Deng, Y. Sun, A. Chakraborty, Y. Lu, J. Brouwer, and P. G. Mehta, “Optimal scheduling of chiller plant with thermal energy storage using mixed integer linear programming,” *2013 American Control Conference*. pp. 2958–2963, 2013.

[99] J. w. Yan, Z. Yu, and X. Zhou, “Study on operation energy efficiency model of chiller based on SVR,” *The 26th Chinese Control and Decision Conference (2014 CCDC)*. pp. 4282–4286, 2014.

[100] Y. Ma, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, and P. Haves, “Model Predictive Control for the Operation of Building Cooling Systems,” *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 3, pp. 796–803, 2010.

[101] G. Stewart and F. Borrelli, “A model predictive control framework for industrial turbodiesel engine control,” *Proc. IEEE Conf. Decis. Control*, pp. 5704–5711, 2008.

[102] Y. Ma, F. Borrelli, B. Hencey, A. Packard, and S. Bortoff, “Model Predictive Control of thermal energy storage in building cooling systems,” *Proc. 48h IEEE Conf. Decis. Control held jointly with 2009 28th Chinese Control Conf.*, pp. 392–397, 2009.

[103] Y. Ma, G. Anderson, and F. Borrelli, “A distributed predictive control approach to building temperature regulation,” *Proc. Am. Control Conf.*, pp. 2089–2094, 2011.

[104] S. Boyd and L. Vandenberghe, *Convex Optimization*, vol. 25, no. 3. Cambridge University Press, 2010.

[105] W. Gang, S. Wang, F. Xiao, and D. Gao, “District cooling systems: Technology integration, system optimization, challenges and opportunities for applications,” *Renew. Sustain. Energy Rev.*, vol. 53, pp. 253–264, Jan. 2016.

[106] S. Huang, W. Zuo, and M. D. Sohn, “Improved cooling tower control of legacy chiller plants by optimizing the condenser water set point,” *Build. Environ.*, vol. 111, pp. 33–46, 2017.

[107] A. Aertgeerts, B. Claessens, R. De Coninck, L. Helsen, and K. U. Leuven, “AGENT-BASED CONTROL OF A NEIGHBORHOOD : A GENERIC APPROACH BY COUPLING MODELICA WITH PYTHON,” pp. 456–463, 2015.

[108] N. R. Patel, M. J. Risbeck, J. B. Rawlings, M. J. Wenzel, and R. D. Turney, “Distributed economic model predictive control for large-scale building temperature regulation,” *2016 American Control Conference (ACC)*. pp. 895–900, 2016.

[109] P. S. Forms, “Horizon 2020 Call : H2020-ICT-2015 Topic : ICT-20-2015 Type of action : RIA Proposal number : 688127 Proposal acronym : DEVELOP Table of contents,” 2015.

[110] H. Peng, *Multivariable Rbf-Arx Model-Based Predictive Control for Nonlinear Systems*, vol. 40, no. 12. IFAC, 2007.

[111] R. Sterling *et al.*, "A virtual test-bed for building Model Predictive Control developments," *Proc. 13th Int. Model. Conf. Regensburg, Ger. March 4–6, 2019*, vol. 157, pp. 17–24, 2019.

[112] L. Zabala, J. Febres, R. Sterling, S. López, and M. Keane, "Virtual testbed for model predictive control development in district cooling systems," *Renew. Sustain. Energy Rev.*, vol. 129, 2020.

[113] I. del Hoyo Arce, S. Herrero López, S. López Perez, M. Rämä, K. Klobut, and J. A. Febres, "Models for fast modelling of district heating and cooling networks," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1863–1873, Feb. 2018.

[114] M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: an engineering perspective," *Int. J. Adv. Manuf. Technol.*, vol. 117, no. 5, pp. 1327–1349, 2021.

[115] B. Houska, H. J. Ferreau, and M. Diehl, "An Auto-generated Real-time Iteration Algorithm for Nonlinear MPC in the Microsecond Range," *Automatica*, vol. 47, no. 10, pp. 2279–2285, Oct. 2011.

[116] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, no. 6, pp. 789–814, 2000.

[117] A. Kelman, Y. Ma, and F. Borrelli, "Analysis of local optima in predictive control for energy efficient buildings," *IEEE Conf. Decis. Control Eur. Control Conf.*, pp. 5125–5130, 2011.

[118] Y. Liao, G. Huang, Y. Ding, H. Wu, and Z. Feng, "Robustness enhancement for chiller sequencing control under uncertainty," *Appl. Therm. Eng.*, vol. 141, no. June, pp. 811–818, 2018.

[119] L. Zabala, J. Febres, R. Sterling, S. López, and M. Keane, "Virtual testbed for model predictive control development in district cooling systems," *Renew. Sustain. Energy Rev.*, vol. 129, p. 109920, 2020.