Energy efficient planning and scheduling of HVAC services in smart buildings

Radhakrishnan, Nikitha

2017

Radhakrishnan, N. (2017). Energy efficient planning and scheduling of HVAC services in smart buildings. Doctoral thesis, Nanyang Technological University, Singapore.

<http://hdl.handle.net/10356/69896>

<https://doi.org/10.32657/10356/69896>

**ENERGY EFFICIENT PLANNING AND
SCHEDULING OF HVAC SERVICES IN
SMART BUILDINGS**

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2016

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor, Prof. Su Rong, for his continuous support throughout my Ph.D. study and research. His patience, motivation, and guidance have helped me grow as a researcher. I would like to thank my co-supervisor, Prof. Kameshwar Poolla, for teaching me the true meaning of good research, for always inspiring, and for all the laughs.

I am grateful for the funding sources that made my Ph.D. possible. I was offered a scholarship for graduate studies by the School of Electrical and Electronics Engineering, Nanyang Technological University and National Research Foundation, Singapore, as part of the Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) project under the Berkeley Education Alliance for Research in Singapore (BEARS).

I would like to thank Irene Yong of BECA Carter Hollings & Ferner S.E.A Pte. Ltd., who was very patient in answering a lot of questions related to my work, which helped better, my understanding of building systems. I am grateful to Dr. Su Yang and Dr. Seshadhri Srinivasan for their guidance through my research.

During the course of my Ph.D., there are a few special people with whom I have shared happy moments and who have helped through bad times. I am extremely grateful for:

- Rahul, Raja, Saurabh, and Kaushik - For being the ones I could always count on and for never hesitating to brutally point out my flaws. Raja, thank you for

always listening. Saurabh, thank you for the numerous hugs. Rahul, thank you for treating me like family. Kaushi, thank you for the positivity and proof-reading this dissertation.

- Antonis - who has been a continuous source of happiness (and free food) in the lab. I thank you for being who you are and for the profound wisdom that you have imparted unto me. Yamas!
- Aarti - For being the most fun and understanding girlfriend I have ever had. Thank you for the Skype sessions.
- Sheetal and Nishanth - For accepting me for who I am without judgment and always being there in the time of need.

Gowtham, your support and understanding have been extremely crucial in my Ph.D. life and otherwise. I would be half as strong and independent as I am today, if not for you. Thank you, for believing in me.

To my sister, Sangeetha, and brother-in-law, Karthik, thank you for the trust and support, the secret-keeping, putting through my craziness and being, probably, the only source of fun in my family.

Most importantly, I would like to thank my parents for the unlimited love and care, and for always stressing the importance of a good education. Thank you for the patience, countless prayers and sleepless nights.

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List of Abbreviations

ACMV Air Conditioning and Mechanical Ventilation

AHU Air Handling Unit

ASHRAE American Society of Heating, Refrigerating and Air Conditioning Engineers

BCA Building and Construction Authority

BEMS Building Energy Management Systems

CAV Constant Air Volume

COP Coefficient Of Performance

CP Centralized optimization Problem

DAM Day Ahead Market

EIA Energy Information Administration

HVAC Heating, Ventilation and Air-Conditioning

LP Linear Programming

MILP Mixed Integer Linear Programming

MPC Model Predictive Control

RCP Revised Centralized optimization Problem

QCQP Quadratic Constrained Quadratic Programming

TBSS Token Based Scheduling Strategy

RTBSS Relaxed Token Based Scheduling Strategy

VAV Variable Air Volume

List of Symbols

Symbol	Description	Unit
A_i	Cross-sectional area of duct branch opening into zone i	m^2
Ar_i	Floor area of zone i	m^2
$\underline{A_i}$	Minimum cross sectional area of duct	m^2
$\overline{A_i}$	Maximum cross sectional area of duct	m^2
b_i	Beginning of the flexibility period for zone i	-
c_i	Thermal capacitance for zone i	kJ/K
c_p	Specific heat of air	kJ/kgK
C_{FIX}	Fixed energy cost	$\$/kWh$
C_{TOU}	Time-of-Use energy cost	$\$/kWh$
d_r	Return to total air ratio	-
e_i	End of the flexibility period for zone i	-
E_v	System ventilation efficiency	-
g_i	Cooling energy supply to zone i	kJ
g_{cap}	Chiller capacity	kJ
H_c	Length of flexibility contract period	-
H_p	Prediction horizon	-
H_w	Time horizon window size	-
i	Zone index	-
k	Sample index	-

k_f	Parameter capturing fan efficiency and duct pressure losses	
$\dot{m}_i$	Cool air mass flow rate into zone i	kg/s
$\dot{m}_{cap}$	Supply fan flow rate rating	kg/s
$\dot{m}_{il}$	Lower limit on air mass flow rate	kg/s
$\dot{m}_{ih}$	Upper limit on air mass flow rate	kg/s
$\dot{m}_{OA}$	Mass flow rate of outside air intake	kg/s
$\dot{m}_{SA}$	Mass flow rate of fan supply air	kg/s
n_z	Number of zones	-
p_0	Pressure at supply fan	Pa
p_{cap}	Pressure rating of supply fan	Pa
p_i	Pressure at entrance of zone i	Pa
p_z	Pressure of air in zone	Pa
P_c	Chiller power consumption	kJ
P_f	Fan power consumption	kJ
Pop_i	Population of zone i	-
$\dot{Q}_i$	Cooling load forecast for zone i	kJ
Q_{ch}	Constant for various amounts of cooling loads	-
R_i	Thermal resistance between zone i and the environment	kW/K
R_a	Outdoor air flow rate required per unit area determined by ASHRAE standard 62-2001	kg/s
R_p	Outdoor air flow rate required per person determined by ASHRAE standard 62-2001	kg/s
T_c	Temperature of cool air supply	°C
T_i	Temperature of zone i	°C
T_m	Temperature of mixed air	°C
T_r	Temperature of return air	°C
T_{il}	Lower thermal comfort bound	°C

T_{ih}	Upper thermal comfort bound	°C
T_{oa}	Temperature of outside air	°C
U_i	Number of flexibility periods for zone i	-
y_i	Binary indicator for the ON status of flexibility for zone i	-
z_i	Binary indicator for the OFF status of flexibility for zone i	-
Zp_i	Primary outdoor air fraction for zone i	-
δ	Sampling time	s
η	Reciprocal of chiller COP	-
η_f	Supply fan efficiency	-
ρ	Air density	kg/m^3

Abstract

The building sector represents at least 40% of the worldwide primary energy consumption and in tropical Singapore, electricity comprises the single largest building operating expense with up to 60% of the energy going into air-conditioning. Much of this energy consumption is wasted. Environmental Protection Agency (EPA) studies suggest that 30% energy savings can be realized through improvements to facilities and facility management.

This work proposes a novel distributed architecture for controlling Heating, Ventilation, and Air conditioning (HVAC) systems in commercial buildings. We regard heating/cooling as a service. The provider of the service is the HVAC system and customers are the thermal zones. Zone Modules in each thermal zone use local models and measurements to compute requests for HVAC service over various future time windows. These requests are expressed in terms of the heating/cooling service required, which we can conceptually regard as tokens. A Central Scheduler balances token requests and allocates tokens to each zone for the next time slot. This allocation attempts to minimize total energy consumption while respecting operational constraints. Zone modules update their local models based on the measured thermal responses resulted from allocated tokens and re-compute forward token requests. This strategy is implemented in a Model Predictive Control framework.

The proposed token based architecture is inspired by medium access control protocols in communication networks and is called Token Based Scheduling Strategy.

It offers several advantages in the context of HVAC systems. The architecture is scalable to large buildings with 200-500 thermal zones, it is robust relative to non-stationary environmental conditions and unanticipated changes in user needs, and it is modular enabling low-cost deployment without requiring expensive custom thermal modeling of buildings. The proposed architecture can readily accommodate a wide variety of operational factors like chiller efficiency through Coefficient of Performance (COP) specifications, as well as constraints on cooling air mass flow rates, fan capacities, duct pressure distribution, and damper opening constraints. Simulation studies reveal that the proposed approach suffers modest performance loss as compared with centralized non-linear scheduling strategies. These centralized strategies, however, are not scalable to buildings with 200+ zones and suffer prohibitive deployment costs.

The token based scheduling strategy is further extended towards minimizing energy costs by incorporating the Time-of-Use electricity pricing strategy. This helps in shifting electricity usage to off-peak periods and reducing energy demand peaks. Further, by arbitraging among consumer comfort margins, buildings can change their energy consumption patterns to provide flexibility to the grid. A new framework for contracting flexibility in buildings that includes temporal constraints and a decentralized approach for computing the online flexibility in buildings is also proposed.

While this strategy has applications to HVAC systems in general, the focus of this thesis will be air-conditioning systems in tropical climates.

Chapter 1

Introduction

World energy consumption has rapidly risen over the past five decades from the increased use of fossil fuels. Singapore has continuously tried to adopt newer and more environment-friendly energy sources to satisfy its electricity demands. First, there was a shift from diesel and fuel oil to the cleaner natural gas and more recently, other energy sources like solar and waste-to-energy are taking over the market. By 2030, Singapore aims to stop the increase in greenhouse gas emissions altogether. The country now consumes around 4000 GWh of electricity in a month.

So where does all the energy go? Globally, the energy consumption can be broken down into three main sectors as shown in Fig. 1.1 [1] and the 2011 breakdown of these end-uses is as follows: buildings 40%, industrial 31%, and transportation 28%. The building sector (commercial and residential) represents in excess of 40% of

Figure 1.1: World energy consumption by sector, 2012 (EIA Data)

Figure 1.2: Breakdown of energy consumption within a building¹

worldwide primary energy consumption, 53% of Singapore electricity consumption, and 38% of carbon dioxide emissions. Energy consumption in the building sector is rising due to the increasing population and economic activities in most parts of the world. Singapore has mandated aggressive energy efficiency targets to be realized by 2030 - 35% improvement over 2005 levels (set by Sustainable Singapore Blueprint) and 80% of buildings to be Green Mark certified (set by Building and Construction Authority).

1.1 Motivation

In Singapore, with its hot and humid climate, electricity comprises the single largest building operating expense with up to 60% of the energy supporting air-conditioning services (Fig. 1.2). A study conducted by Building and Construction Authority of Singapore (BCA) on 36 commercial buildings found that an efficient air-conditioning system can reduce a building's overall energy consumption by 16% per year. In monetary terms, this amounts to savings of \$22.7 million per year making it crucial to focus on energy reduction and significant improvement of energy efficiency in commercial buildings while satisfying human comfort demands.

¹N. C. C. Secretariat and S. National Research Foundation, "Air-con system efficiency primer: A summary"

Figure 1.3: Energy consumption breakdown for HVAC Systems¹

The approximate distribution of the energy consumption within HVAC systems is 55% for the chiller, 35% for fans, 5% for pumps, and 5% for cooling towers. The effort to reduce energy consumption in building Heating, Ventilation, and Air Conditioning (HVAC) systems is constrained by human comfort and air quality requirements. The American Society of Heating, Refrigerating and Air-conditioning Engineers, Inc. (ASHRAE) defines human thermal comfort as “the state of mind that expresses satisfaction with the surrounding environment” (ANSI/ASHRAE Standard 55). It must be noted that thermal comfort includes not only the temperature, but also factors like humidity and pressure. ASHRAE has developed an internationally accepted standard to describe comfort requirements in buildings. However, due to its special tropical climate, Singapore has to follow its own standard SS553:2010 (an adapted version of the ASHRAE standard) where the recommended indoor temperature is 23°C to 25°C, and the relative humidity is not more than 65% [2].

Commercial buildings in Singapore are adopting highly efficient HVAC systems. This dissertation provides a computationally viable and financially affordable strategy for reducing the energy consumption of HVAC systems in large commercial

buildings without sacrificing occupants' comfort. The proposed methodology is robust to the unpredictable weather conditions of Singapore and uncertainties in occupant thermal demands. Building automation systems that help to manage energy use and improve comfort by efficiently controlling its operations can help to create a 'greener' Singapore.

1.2 Literature review

The potential for dramatic gains in building efficiency through intelligent management of HVAC systems in commercial buildings has led to considerable recent research activities [3–11]. Energy efficiency measures, however, must guarantee thermal comfort and indoor air quality standards [12–16]. Any viable approach must be cost-effective in deployment to diverse building stock and scalable to large structures with 300 zones or more.

In the current literature, there are two different strategies for building HVAC management. The first strategy is to use an advanced control to ensure that zone temperatures follow pre-specified set-point trajectories (with possible fluctuations that fall in a comfort band) while minimizing the energy consumption of the process. Most of these approaches design a model predictive controller due to their ability to incorporate real-time weather, occupancy, and thermal comfort information in system models and suppress disturbances [17–21]. Noticeable work in this direction can be found in [22–25] that handles complex constrained multi-variable problems and uncertainties. Model-predictive control methods have also been studied to optimize pre-cooling strategies. Pre-cooling zones in advance of their occupancy offers an attractive strategy for energy efficiency gains [26,27] and serves to shift loads by exploiting demand temporal flexibility and the natural thermal mass in zones [28–32].

Many HVAC control methods are centralized, which involve sophisticated opti-

mal control methods and aim to minimize the total energy consumption across all zones [33–36]. Centralized controllers optimizing both fan and chiller energy consumptions while regulating the zone temperatures has been widely studied in the literature [37–39]. A comparison of different MPC strategies with emphasis on Stochastic Nonlinear MPC is given in [25,40–43]. Kelman and Borrelli [22] propose an MPC approach to minimize energy use and satisfy occupant constraints using a sequential quadratic programming algorithm. This technique provides a locally optimal solution, which reproduces other scheduling strategies like pre-cooling, but the computational complexity is unfavorable when applied to large buildings. Implementing centralized approaches requires solving complex large-scale nonlinear optimization problems, which is computationally intractable. Furthermore, it raises robustness and communication bandwidth issues.

Distributed control is discussed in [44–47], to better address the computational challenges associated with large building systems. Distributed approaches overcome the shortcomings of centralized approaches by optimizing the fan energy consumption in the individual zones [47–51]. Predictive occupancy-based control is described in [52–54]. Distributed approaches using dual-decomposition [47], affine quadratic regulator [50], affine disturbance feedback [55], and stochastic scenario-based strategies [44] have been studied in the literature. Though distributed approaches in literature offer good scaling and low complexity, the chiller power is not considered in their formulation. Furthermore, the influence of the room size, occupancy, and user interference on the energy optimization has not been studied in these investigations and will be considered in this thesis.

The second strategy is to utilize scheduling techniques, some of which are described in [56]. For example, (a) the *interruption technique* aims to switch an HVAC off for several hours during the service period; (b) the *early switch off technique* intends to turn the HVAC system off a few hours before the end of the service period so that

the remaining cooling energy in the building can satisfy the occupants' need just by the end of the service period; (c) the *demand reduction technique* advocates starting cooling during the off-peak period (e.g., from 20:00 to 08:00) to store cooling energy in the building, which can reduce the cooling demand during the peak hour and enjoy low off-peak period electrical pricing; and (d) the *alternative switch on/off technique* is to turn an HVAC off on a regular basis during the service period (e.g. every 30 minutes or one hour), to fully utilize cooling energy stored in the building. Conventional scheduling techniques include the *baseline technique* [57], which divides the whole day into night setback and occupied hours and assigns temperature set-points accordingly; and the *step-up technique* and the *line-up techniques* [58,59], which increase the temperature set-points a few times during the occupied hours in terms of a step-up pattern and a linear pattern, respectively. Advanced scheduling techniques include *extended precooling with zone temperature reset* [60], which precools a building a few hours before the occupied hours, increases the set-point by one or two degrees to lower the energy consumption, and increases the set-point even higher during the peak hours; *5-period division scheduling* [24], which has a finer partition on the ACMV night setback and occupied hours to have more choices on the temperature set-points; *aggressive duty cycling* [61], which is similar to the alternative switch on/off technique, except that in the former case advanced sensor technologies are used to decide when to turn the HVAC off and when to turn it on without making occupants feel uncomfortable; and *optimal demand-limiting set-point trajectories* [62], which is similar to the step-up and line-up techniques, except that the choice of the temperature increasing trajectory is carefully chosen to further reduce energy consumption. The effectiveness of some aforementioned scheduling techniques is discussed in [63]. Predictions of factors that affect HVAC system operations are used in planning HVAC services. Demand Controlled Ventilation (DCV) is the use of occupancy predictions to control ventilation [64,65]. Weather predictions

and knowledge of future thermal loads help in increasing human comfort levels. As accurate forecasts are difficult to obtain, Model Predictive Control (MPC) methods have been explored to optimize scheduling strategies [40,66,67]. These methods can effectively handle multi-variable problems and uncertainties.

We find that these existing approaches have three major shortcomings: (a) high computational complexity, which limits scalability, (b) little coordination of fans and the chiller system, which leads to suboptimal energy savings, and (c) use of centralized architectures and user-calibrated models, which makes deployment costs prohibitively high.

Buildings equipped with energy efficient controllers should also work in synergy with the electric grid. Smart buildings ready to be interconnected with smart grids should incorporate capabilities like smart metering, demand response, interoperability, etc. [68]. While the use of model predictive controllers for energy savings has been widely investigated in literature [37–39,42,54,69–74], the deregulation of electricity markets is further compounding the interest on this topic. Designing predictive controllers using pricing information is relatively new for multi-zone buildings. Furthermore, most existing results design centralized MPCs with an aim to reduce the overall energy consumption of an HVAC system, e.g. fan plus chiller power or sum of total and peak air-flow rates are reported in [55,75].

The use of pricing information within centralized MPC has been investigated only in [76–78]. The complexity associated with such centralized schemes is quite high due to the need for frequent information exchanges between the zones and the central controller, and the high computational effort required at the central controller. Distributed approaches, wherein local controllers solving the zone optimization problem in parallel, overcome the difficulties with the centralized approaches [47,48,50,79,80].

Currently, consumption and generation patterns of the electric grid are becoming less predictable due to the introduction of new entities such as electric vehicles,

storage systems, and renewable energy within the energy grid. As a result, grid operators use ancillary services to procure such intermittent generations on fast time-scales. Consequently, utilities are looking for additional flexibility to handle energy peaks and also for performing ancillary services such as load balancing [69,81]. This provides an opportunity for customers to reduce their electricity bills by trading flexibility using an aggregator (a group of buildings).

Using flexibility from the buildings requires exploiting its thermal storage property by prior planning of the HVAC system operations [82]. The role of building flexibility in providing frequency regulation has been studied in [69,83]. However, the analysis is limited to the aggregator viewpoint. A distributed approach, using an agent-based approach is studied in [84]. The use of dynamic contracts that looks beyond the aggregator level for selling the flexibility was studied in [85]. Moreover, the triggers sent by aggregators are time-varying [84] and the user cannot decide proper time slots for providing the flexibility. On the other hand, contracts are expected to have provisions for a customer to decide the time for providing the flexibility. This is an important feature of the contract that can promote consumer participations. Next, the existing approaches lean more towards the building level and a centralized solution is generally studied. While the contractual framework promotes scalability, the idea of performing central computation in a multi-zone buildings rather limits this advantage. Using decentralized approaches wherein the individual zones compute the flexibility contracts simplifies the computation to a great extent. Furthermore, only zones providing flexibility need to perform computations in a multi-zone buildings at any given time. Integrating flexibility choices within contracts with a decentralized solution methodology has not been studied in the literature.

To overcome the above-mentioned shortcomings, this thesis presents a novel hierarchical distributed architecture for controlling HVAC systems in commercial build-

ings. The proposed strategy minimizes energy consumptions of chiller and fans, while reducing energy costs by taking advantage of pricing information published by the service provider and earning revenue by providing flexibility services to the electric grid.

1.3 Contributions

This thesis contains the following contributions to the field of smart buildings:

1. A new conceptual idea of token request and allocation for HVAC scheduling in commercial buildings is proposed. We regard heating/cooling as a *service*. *Zone Modules* in each thermal zone use local information and models to request *tokens*, i.e., a specific amount of cool air, across various forward windows. These computations are distributed and can be solved efficiently, even though within each zone we need to solve a small-scale non-convex quadratic constrained quadratic programming problem. A *Central Scheduler* balances token requests and allocates tokens to each zone for the next time slot. Under some modest assumptions about the fan energy profile and duct air distribution, this can be formulated as a two-step optimization process solving a mixed integer linear programming problem and a convex quadratic constrained quadratic programming problem. Zone Modules update their local models and adaptively recompute forward token requests based on the fresh information. This strategy is implemented in a Model Predictive Control (MPC) framework.
2. Existing scheduling techniques ignore operational constraints like the chiller coefficient of performance, damper position, and duct pressure constraints as its inclusion will increase computational complexity. The proposed token based scheduling strategy effectively includes these constraints and gives a more realistic scheduling solution for better energy savings.

3. Due to such high computational efficiency, the token based scheduling strategy offers several advantages compared with other existing approaches. First of all, it is scalable to commercial buildings with hundreds of zones under a variety of constraints about cool air generation, distribution, and delivery. Secondly, the Zone Modules are robust to the varying environmental conditions and unanticipated changes in occupant needs. The fast computation at both the Zone Module and Central Scheduler levels ensure satisfaction of the temperature demands and human comfort levels. Lastly, there is a very low deployment cost for this algorithm requiring no changes to the already existing building controls.
 4. A major concern is whether the token-based solution may lead to a total HVAC energy consumption that is far away from the truly optimal one. In other words, it is necessary to understand how to measure the quality of the solution in terms of its “distance” from the globally optimal one. Since it is practically infeasible to determine the actual globally optimal solution due to the expected high computational complexity, a specific method to derive a lower bound on the globally optimal HVAC energy consumption is presented.
 5. The token based scheduling strategy is implemented with a closed loop using the building simulation software EnergyPlus (<https://energyplus.net/>). The software receives inputs on the building construction, occupant comfort, thermostat settings and weather forecasts and calculates various building parameters. The ones that are of importance to this work are the zone temperature profiles, mass flow rate of cool air and energy consumption patterns of various components. Historical data is used for building zone thermal models to be used in the scheduling algorithm. After every token allocation, the thermal response is measured and fed into the model identification block for
-

updating thermal models before computing token requests for the next iteration.

6. Energy costs are included in the scheduling algorithm for minimizing electricity costs in addition to energy consumption. This not only decreases electricity costs for the building owners but also helps the grid shift the peak demand to off-peak times and reduce the peak to average ratio of the power consumption. In such cases, the zone controllers optimize the energy cost whereas central controller tries to reduce the energy consumption of the whole building.
7. Finally, an investigation is conducted, into a new framework for contracting flexibility in buildings that include temporal constraints. A decentralized approach for computing the online flexibility in buildings is presented where occupants can define flexibility and its timings.

1.4 Thesis Overview

The thesis consists of 7 chapters and its organization is described below:

Chapter 2: This chapter explains the general working of a building HVAC system along with detailed explanations of its major components. The working and models for the components used in this thesis are described in detail. It also provides the general control problem of HVAC systems in commercial buildings.

Chapter 3: In this chapter, a simplified formulation of the token based scheduling strategy is presented. The architecture and flow of information in the scheduling strategy is explained and the various stages of the scheduling strategy are described. Typical simulation results are provided and a comparison of the results with existing centralized strategies and the legacy Singapore cooling strategy is conducted.

Chapter 4: In this chapter, the token based scheduling strategy is extended to incorporate operational constraints like the chiller efficiency, chiller capacity, duct network, and damper position constraints. Ventilation requirements are calculated using information about zone size and occupancy. Simulation results to establish the advantages of the method are also provided.

Chapter 5: This chapter explains the construction of a building model through the building simulation software, EnergyPlus. The models obtained from this software are used to validate the energy savings obtained from the token based scheduling strategy. comparison between the token scheduling and the centralized control strategies are also made using the EnergyPlus building models.

Chapter 6: Energy costs are incorporated into the token based scheduling strategy. Fixed and Time-of-Use pricing strategies are used in the token based scheduling and centralized strategies. The results for both are compared to analyze the cost savings obtained from incorporating energy costs. A comparison is also made with the default thermostat control obtained from EnergyPlus. This chapter also presents a contractual framework to trade flexibility in multi-zone buildings, incorporating temporal constraints that reflect the user preferences on the flexibility. That is, the individual zones in the building specify the flexibility as well as the timing preferences for providing services to the grid within a contracting period.

Chapter 7: The conclusions and future work of this thesis are presented in this chapter.

Chapter 2

Description of HVAC Systems

Space conditioning is a broad term that describes the process of maintaining acceptable conditions of temperature, humidity, ventilation, air quality, and air distribution within a space. Over the years, air conditioning has changed from just maintaining a set temperature to effectively controlling the above-mentioned parameters. In a building, this process is usually referred to as HVAC, which is Heating, Ventilation, and Air Conditioning. In commercial buildings, HVAC is an essential consideration in maintaining the productivity, comfort, and health of occupants. If air quality and temperature are not maintained, occupant comfort in the workplace can suffer, directly affecting productivity and morale. The following processes can be found in any air conditioned space:

1. Heating - Adding thermal energy to a space
2. Cooling - Removing thermal energy from a space
3. Humidifying - Increasing relative humidity by addition of water vapor or steam
4. Dehumidifying - Decreasing relative humidity by removal of water vapor
5. Filtering - Removing dust, pollens, smoke, and other contaminants from air

6. Ventilating - Adding external air for maintaining freshness
7. Air movement - Controlling movement of supplied air to suit occupant comfort

In Singapore, air-conditioning systems can be broadly classified into:

1. Unitary air-conditioning systems - self-contained air units like split room units, packaged units, etc.
2. Central air-conditioning systems cooled indirectly by chilled water. These systems are further classified into:
 - All-air systems - Circulate air treated in a central location to the conditioned space. Such systems include Constant Air Volume (CAV) systems and Variable Air Volume (VAV) systems.
 - Air-water systems - Circulate chilled water to fan coils and induction units located in the conditioned space.

This thesis concentrates on the more popular VAV HVAC systems for commercial buildings. The advantages of VAV systems over constant-volume systems include increased efficiency, low cost, reduced compressor wear, lower energy consumption by system fans, less fan noise, and additional passive dehumidification. VAV systems can also precisely meet the comfort requirements of different zones in a building without heating and cooling at the same time.

2.1 Description of an Air Distribution System

The schematic of a typical Variable Air Volume (VAV) Heating, Ventilation, and Air Conditioning (HVAC) system is offered in Fig. 2.1. The Air Handling Unit (AHU) takes outside air and performs multiple functions like filtration, temperature control, humidity control, etc. After passing through the filters, the air is mixed

Figure 2.1: Typical Variable Air Volume Ventilation and Air Conditioning System of a commercial building in Singapore

with return air from inside building spaces. From an energy efficiency point of view, for a cooling system, complete recirculation of return air is preferred as it is much colder than outdoor air. But the intake of outdoor air is vital for maintaining indoor air quality for occupants. The mixed air passes through cooling coils that circulate chilled water supplied by the chillers. The mass flow rate and temperature of the chilled water are controlled to ensure that the air is cooled to a predetermined temperature, suitable for cooling zones. The warm air rejects heat to the chilled water in cooling coils in the AHU and is forced by supply fans into the building's duct network. The pressure rise at the fan depends on the required mass flow rate of supplied cool air, which in turn is determined by cooling demands of the building. The supply air reaches zones through the building duct network.

A zone is a conditioned space inside a building that is regulated by a single thermostat. The duct openings to the zones are fitted with a set of metal plates called dampers that control their cross-sectional areas, affecting the flow rates of cool air entering the zones. When cool air is supplied to the zone, a portion of the existing air is pushed into the return duct. Within a zone, the incoming cool air mixes

with the existing air reducing the overall zone temperature. A portion of the total return air is fed into the mixing chamber, while the rest is vented to the outside. Some conditioned spaces like laboratories have return ducts that do not mix with the return air from the rest of the building to avoid any synthesized pollutants from being recirculated within the building.

The bulk of the energy consumption in a building is expected in the chiller system (around 60-70%), while most of the remainder is used by the fans in the AHUs. The energy consumption in other system components (for example, pumps) is negligible, and being relatively fixed, offers a modest potential for efficiency gains.

2.2 Component Models

This work concentrates on commercial buildings, where relatively fixed working hours and temperature set-points for zones render a sufficiently good model. Humidity is not considered, as the dehumidification process does not affect the energy consumed due to cooling. It is also assumed that the air mixing inside building spaces is sufficiently quick, e.g., it can be done within each sampling period for a discrete-time treatment, which is usually true, considering that each sampling period typically takes about 15-30 minutes. Finally, it is assumed that local weather forecast data is accessible for good short-term predictions.

2.2.1 Zone Thermal Model

Optimal control/scheduling of building HVAC systems requires models to capture the thermal dynamics of zones and their interactions with the building structure. Several papers have dealt exclusively with developing thermal models of varying fidelity for zones that are suitable for various building control strategies [42,86–89]. Approaches range from lumped electric circuit equivalent models for thermal

zones [90,91] to detailed prediction models that account for a wide variety of factors including lighting, occupancy, and climate [92–94]. A simple first order energy balance equation is used for this dissertation. The bilinear thermal model decouples thermal dynamics across zones:

$$c_i \dot{T}_i = \dot{m}_i c_p (T_c - T_i) + R_i (T_{oa} - T_i) + \dot{Q}_i \quad (2.1)$$

where T_i is the temperature of zone i , c_i is the thermal capacitance of zone i , $\dot{m}_i$ is mass flow rate of cool air supplied to zone i , c_p is the specific heat capacity of air, T_c is temperature of cool air, $\dot{Q}_i$ represents the forecasted load due to thermal input from internal loads, occupants as well as coupling with adjacent zones, and R_i is a constant that represents thermal conductance between zone i and the environment. Forecasts of the ambient temperature T_{oa} are also available through weather predictions. Interactions across zones are treated as disturbances in the cooling load term $\dot{Q}_i$, allowing us to consider each zone independently. Assuming $\dot{m}_i$ and $\dot{Q}_i$ are zero-order held at sampling rate δ , this model is discretized as follows:

$$T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 c_p \dot{m}_i(k) (T_i(k) - T_c) = v_i(k) \quad (2.2)$$

where

$$\alpha_1 = \frac{\delta R_i}{c_i} - 1, \alpha_2 = \frac{\delta}{c_i}, v_i(k) = \frac{\delta}{c_i} (\dot{Q}_i(k) + R_i T_{oa}(k)).$$

Here, k is the sample index, and i is the zone index with $i = 1, \dots, n_z$. A new variable g_i is introduced, which is interpreted as cooling energy supplied to zone i , i.e.,

$$g_i(k) = \dot{m}_i c_p (T_i(k) - T_c). \quad (2.3)$$

With this substitution, the zone dynamics become linear:

$$T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 g_i(k) = v_i(k).$$

We assume that the temperature set-point demands for each zone are specified in advance. Instead of a strict set-point, the following range of temperatures are used that are within human comfort requirements:

$$T_{il}(k) \leq T_i(k) \leq T_{ih}(k), \quad (2.4)$$

where T_{il} and T_{ih} are the lower and upper bounds of a comfortable temperature range for zone i . We will employ a model predictive control strategy to deal with both increasing forward uncertainties in these forecasts and abrupt changes in the acceptable temperature ranges (possibly from occupancy forecasts or sensors).

2.2.2 Zone Dampers and Duct network

The duct network of an HVAC system is the static component of the installation and connects all parts of the building via supply air and exhaust air flow. The supply fan is responsible for creating enough pressure rise to ensure that the mass flow rates of cool air supplied to the zones comply with the demands. Usually, the fan in the AHU has enough capacity to serve every zone in the building at the same time. Consequently, it is safe to assume that an insufficient pressure rise will not occur at the fan. Duct dimensions need to be designed to obtain the required airflow inside the duct and to ensure that the energy supplied is sufficient to overcome pressure losses during normal operations of the installation. Due to varying friction factors of materials, the type of material (galvanized steel, fiberglass, insulated flexible fabric) must also be considered in the design process.

Duct openings into zones are fitted with a set of adjustable metal plates called

Figure 2.2: Johnson Controls VD-1640 Stainless Steel Damper and Reflectix Insulated duct

Figure 2.3: Sample schematic of a supply air duct network

dampers to control the air flow into the zone by changing its cross-sectional area.

In the formulation presented in this thesis, the mass flow rate profile of every zone is scheduled and the pressure rise and the damper positions are ensured to match these requirements. The pressure rise at supply fans is small relative to atmospheric pressure and so air density can be treated as constant for the process. A sample schematic of the duct network is presented in Fig. 2.3. p_0 is the pressure at the exit of the supply fan while p_i to p_{n_z} are the pressure values at the point, where duct network branches into corresponding zones.

The pressure difference between any two points in the duct system is given by the expression [95]:

$$\Delta p = a \frac{\dot{m}^2}{A^{5/2}}, \quad (2.5)$$

where a is a constant, A is the cross sectional area of the duct, and $\dot{m}$ is the mass flow rate of the passing fluid.

- **Main duct:** In the main duct the pressure can be described as follows:

$$\Delta p = f \dot{m}^2, \quad (2.6)$$

where $f = \frac{a}{A^{5/2}}$ is a constant. Pressure decreases from p_0 to p_{n_z} in the main duct, where n_z is the number of zones, p_i is the pressure at zone i , and p_0 is the pressure at the supply fan outlet. Considering a particular mass flow rate profile that has to be satisfied for the network, the corresponding pressure requirements at the main duct will be given as follows:

$$p_{i+1} - p_i + f_i \left(\sum_{q=i+1}^{n_z} \dot{m}_q \right)^2 = 0 \quad i = 0, 1, 2 \dots n_z - 1. \quad (2.7)$$

This equation gives the relationship between the pressure in the duct and the mass flow rate of cool air flowing through it in the absence of dampers or when all dampers are in the fully open position. As there exists an extra control in the duct branches that open into zones through dampers, we are free to increase the pressure in the main duct and accordingly adjust the damper positions in the zones if required. Even if the pressure is increased in the duct network, the same cool air mass flow rate profile could be maintained by closing dampers at the zones accordingly. Thus, the pressure distribution and the actual cool air mass flow rates satisfy the following inequality throughout the main duct:

$$p_{i+1} - p_i + f_i \left(\sum_{q=i+1}^{n_z} \dot{m}_q \right)^2 \leq 0 \quad i = 0, 1, 2 \dots n_z - 1. \quad (2.8)$$

- **Duct branches into zones:** The pressure of every zone is known in advance. Without loss of generality, they are assumed to be the same, say p_z . At every duct opening into a zone, there is a damper fitted, which alters the cross sectional area A_i of the duct in order to control the mass flow rate of cool air passing through it. The pressure equation for the openings into the zones fitted with a damper is given as follows:

$$p_i - p_z = a_i \frac{\dot{m}_i^2}{A_i^{5/2}}, \quad (2.9)$$

where A_i is the cross sectional area of the duct for zone i . Equivalently, the above equation can be represented with inequalities as follows:

$$\dot{m}_i^2 \geq \frac{A_i^{5/2}}{a_i} [p_i - p_z], \quad (2.10)$$

$$\dot{m}_i^2 \leq \frac{\overline{A}_i^{5/2}}{a_i} [p_i - p_z], \quad (2.11)$$

where $\underline{A}_i$ is the minimum cross sectional area of duct and $\overline{A}_i$ is the maximum cross sectional area of duct.

All inequalities mentioned above will be treated as duct and damper position constraints in the HVAC scheduling formulation to follow.

2.2.3 Fan

HVAC systems typically use either axial or centrifugal units equipped with variable frequency drives to allow a wide range of air flow rates. The power consumed by the fan depends mainly on the mass flow rate of the fluid supplied and the pressure difference Δp between inlet and outlet.

$$P_f = \left(\sum_{i=1}^{n_z} \dot{m}_i \right) \frac{\Delta p}{\rho \eta_f}, \quad (2.12)$$

Figure 2.4: Centrifugal fan - Kruger Ventilation Fan BSB Series

where ρ is the air density and η_f is the fan efficiency. As described in [22], if damper positions are fixed, $\Delta p \propto (\sum_{i=1}^{n_z} \dot{m}_i)^2$. This relation is not true when the dampers change positions. When they are opened, the pressure drop increases more slowly than the total flow squared. Thus, a quadratic fan power model is commonly used [22]:

$$P_f = k_f \left(\sum_{i=1}^{n_z} \dot{m}_i \right)^2, \quad (2.13)$$

where k_f is a parameter that captures both the fan efficiency and the duct pressure losses. The capacity of each fan must be considered in each application, which will be one constraint in the HVAC scheduling formulation.

2.2.4 Chiller

The chiller system is the key component of a building HVAC system. It is responsible for removing heat from building spaces. The chiller provides a continuous supply of chilled water to the cooling coils in the AHU. Warm air passes over these coils inside the AHU producing cool air that serves to cool zones. In Singapore, the typical temperature of the chilled water is between $4^\circ - 7^\circ\text{C}$ and the temperature

Figure 2.5: Schematic of a typical chiller plant working

of the cool air at the exit of AHU is $12^{\circ} - 14^{\circ}\text{C}$.

The working of a chiller is straightforward. Chilled water in the cooling coils, absorb heat from the warm air passing over it. The flow rate of the chilled water is adjusted according to the flow rate of the supply air and the temperature to which it needs to be cooled. The warmer chilled water now flows into an evaporator, where it rejects heat to a refrigerant. Chilled water is pushed through tubes to keep it from mixing with the refrigerant. The refrigerant turns into vapor, which is sucked into a compressor to convert back to a liquid. Finally, the liquid refrigerant leaves the condenser tank and is supplied to cooling towers. At the cooling towers, the refrigerant is sprayed at a height and comes into contact with air blown through the towers by fans. The refrigerant cools down and is supplied back to the condenser to absorb more heat from the chilled water loop. The loops continue to constantly serve the building cooling demands. A schematic of the chiller plant working is presented in Fig. 2.5 adapted from [33].

Large buildings are equipped with multiple chillers operating in parallel to meet large cooling requirements. The most important factor that decides the performance of the chillers is the load carried by each operating chiller. A variety of chiller sequencing control methods is practiced for switching the chillers on and off [32,

Figure 2.6: A typical chiller plant COP curve. Data obtained from Beca Carter Hollings & Ferner S.E.A Pte. Ltd.

96]. At any time instant, the capacity of all turned-on chillers should meet the cooling demand in an energy efficient manner. The total cooling load-based chiller sequencing control strategy determines the thresholds according to the building instantaneous cooling load and the maximum chiller cooling capacity, which is in principle the best approach for chiller sequence control [97,98].

In this dissertation, chiller sequencing is expressed in terms of adjusting the coefficient of performance (COP) based on the building cooling load measurable at the cooling coils. The COP is the ratio of provided heating or cooling to the total consumed electrical energy. Higher COPs equate to lower operating costs. In the model used for this dissertation, the COP of the chiller system is approximated as a piecewise constant function of the building cooling load adapted from the data given by BECA Carter Hollings & Ferner S.E.A Pte. Ltd. as shown in Fig. 2.6. In order to determine the total electrical power consumption based on the estimated building cooling load, the reciprocal of the COP, denoted as η is used. Recall that g_i is the cooling energy provided to zone i . Thus, the total building cooling load can be represented as $\sum_{i=1}^{n_z} g_i(k)$.

Let $\{Q_{chi}|i = 1, \dots, n_j - 1\}$ be known thresholds for chiller sequencing obtained from chiller manufacturer curves similar to the right side of Fig. 2.6. The reciprocal of the COP is defined as below.

$$\eta(k) = \begin{cases} \eta_1 & \text{if } \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch1} \\ \eta_2 & \text{if } Q_{ch1} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch2} \\ \eta_3 & \text{if } Q_{ch2} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch3} \\ \vdots & \\ \eta_{n_j} & \text{if } \sum_{i=1}^{n_z} g_i(k) > Q_{ch(n_j-1)} \end{cases} \quad (2.14)$$

Chiller power consumption models are complex, which depend on the particular technology used. One very popular model was proposed by Stoecker [99], which was one of the products of mixing basic heat exchanger theories and polynomial fittings with specific coefficients deduced from manufacturers' data. This has been used directly in a few works [36,100]. Braun *et al.*, in the year 1987, proposed a model that is quadratic in the chiller cooling load and the temperature difference between the leaving and returning chilled water flows [101], which is still widely used, e.g., in software like TRNSYS. In this dissertation, a simple control-oriented model drawn from [22] is used. The model is based on the amount of energy used by the cooling coils in terms of the thermal energy exchanged with the air-side of the plant:

$$P_c = c_p \eta \sum_{i=1}^{n_z} \dot{m}_i (T_m - T_c), \quad (2.15)$$

where η is the reciprocal of the COP, d_r is the return-air-to-total-air ratio, the mixed air temperature is

$$T_m = (1 - d_r)T_{oa} + d_r T_r$$

, and the return air temperature is

$$T_r = \frac{\sum_{i=1}^{n_z} \dot{m}_i T_i}{\sum_{i=1}^{n_z} \dot{m}_i}$$

. By substitution, the power consumption of the chiller becomes:

$$P_c = c_p \eta \left((1 - d_r)(T_{oa} - T_c) \sum_{i=1}^{n_z} \dot{m}_i + d_r \sum_{i=1}^{n_z} \dot{m}_i (T_i - T_c) \right). \quad (2.16)$$

The power function is not linear in the mass flow rate $\dot{m}_i$ as the zone temperature T_i also depends on $\dot{m}_i$ through the zone thermal model.

Besides the chiller COP, the chiller capacity is another constraint that needs to be considered. The chiller capacity can be expressed in terms of the cooling load it can serve g_{cap} . Then,

$$\sum_{i=1}^{n_z} g_i \leq g_{cap} \quad (2.17)$$

2.2.5 Return air-Total air Ratio d_r

The ventilation requirements of a building are represented by the parameter d_r in the chiller cost function. In existing literature [102], a preset value $d_r = 1$ has been used for unoccupied periods and, $d_r \neq 1$ otherwise. Using ASHRAE standards, the amount of fresh air required in each zone is calculated first, according to its expected occupancy and the floor area.

$$Zp_i = \frac{R_p Pop_i + R_a Ar_i}{\dot{m}_i}$$

where Zp_i is the primary outdoor air fraction for zone i , Pop_i is the population of zone i , R_a is the outdoor air flow rate required per unit area determined by ASHRAE standard 62-2001, and R_p is the outdoor air flow rate required per person determined by ASHRAE standard 62-2001. The value of $\max(Zp_i)$ decides ventilation efficiency E_v . The value of E_v can be obtained by interpolating the values given in Table 6.3 of ASHRAE standard 62-2001. The total outdoor air intake flow rate can then be

calculated as:

$$\dot{m}_{OA} = \frac{1}{E_v} \left(\sum_{i=1}^{n_z} R_p P_{op_i} + \sum_{i=1}^{n_z} R_a A r_i \right) \quad (2.18)$$

The difference between the supply air rate and the required outdoor air rate gives the mass flow rate of return air. d_r is the ratio of return air to supply air and it represents the ventilation requirements of the building,

$$d_r = \frac{\dot{m}_{SA} - \dot{m}_{OA}}{\dot{m}_{SA}}, \quad (2.19)$$

where the occupancy and size of zones give the total fresh air requirement $\dot{m}_{OA}$ from Eq.(2.18) and the optimization algorithm gives the cool air supply $\dot{m}_{SA}$. Thus, the required ventilation is brought into the HVAC scheduling problem directly through d_r .

2.3 The General Building Control Problem

Based on the aforementioned component models, this dissertation deals with the following statement of a building HVAC scheduling problem. Let δ be a pre-chosen sampling time and $H_p \in \mathbb{N}$ be a pre-chosen scheduling horizon, where $\mathbb{N}$ is the set of all natural numbers.

Objective: To minimize the sum of power consumed by the chiller (P_c from Eq. 2.16) and supply fan (P_f from Eq. 2.13), i.e.,

$$\min \sum_{k=0}^{H_p} (P_c(k) + P_f(k)) \delta$$

Under the following **constraints:**

1. **C1:** Zone thermal dynamics constraints:

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 g_i(k) = v_i(k).$$

2. **C2:** Zone thermal comfort set-points:

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) T_{il}(k) \leq T_i(k) \leq T_{ih}(k).$$

3. **C3:** Chiller sequencing, i.e., constraints on (the reciprocal of) the COP:

$$\eta(k) = \begin{cases} \eta_1 & \text{if } \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch1} \\ \eta_2 & \text{if } Q_{ch1} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch2} \\ \eta_3 & \text{if } Q_{ch2} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch3} \\ \vdots & \\ \eta_{n_j} & \text{if } \sum_{i=1}^{n_z} g_i(k) > Q_{ch(n_j-1)} \end{cases}$$

4. **C4:** Duct pressure distribution constraints:

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) p_i(k) - p_z = a_i \frac{\dot{m}_i(k)^2}{A_i(k)^{5/2}},$$

and

$$p_{i+1}(k) - p_i(k) + f_i \left(\sum_{q=i+1}^{n_z} \dot{m}_q(k) \right)^2 \leq 0 \quad i = 0, 1, 2, \dots, n_z - 1.$$

5. **C5:** Fan capacity constraint:

$$(\forall k : 0 \leq k \leq H_p) p_0(k) \leq p_{cap},$$

where $p_0(k)$ is the duct inlet pressure, and p_{cap} is the maximum inlet pressure

that a fan can supply. The fan capacity constraint can also be expressed in terms of maximum mass flow rate of air it can supply $\dot{m}_{cap}$.

$$(\forall k : 0 \leq k \leq H_p) \sum_{i=1}^{n_z} \dot{m} \leq \dot{m}_{cap},$$

6. **C6:** Chiller capacity constraint:

$$(\forall k : 0 \leq k \leq H_p) \sum_{i=1}^{n_z} g_i(k) \leq g_{cap},$$

where g_{cap} is the maximum cooling energy the chiller can supply.

7. **C7:** Zone mass flow rate constraint:

$$(\forall k : 0 \leq k \leq H_p) \dot{m}_{il}(k) \leq \dot{m}_i(k) \leq \dot{m}_{ih}(k),$$

Decision variables: $p_o(k), \dot{m}_i(k), p_i(k) \forall i, k$

This problem is highly nonlinear, and difficult to be solved in a centralized manner in real time. For a realistic building with a sufficient number of zones, existing distributed approaches such as Lagrangian relaxation and convex approximation plus ADMM also cannot solve it in real time. In the next chapter, a novel hierarchical distributed strategy called *token-based scheduling* is presented, which can efficiently solve the problem in a sub-optimal manner. The centralized nonlinear optimization approach will be regarded as the benchmark to assess the sub-optimality of the token-based scheduling approach.

2.4 Summary

This chapter describes mathematical models for various HVAC components in commercial buildings. They represent the thermal energy transfer in zones, duct

pressure profile, zone damper position and cool air supply constraints, energy consumed by fans and chiller, and chiller efficiency. These models are used to define the general HVAC scheduling problem along with the constraints under consideration in this dissertation. The following chapter describes a new HVAC scheduling strategy for minimizing energy consumption while satisfying human comfort in large buildings.

Chapter 3

Brief Sketch of the Token Based Scheduling Strategy

In this chapter, an intuitive form of the token-based scheduling strategy associated with its engineering implementation is presented. This is to ensure that the reader understands the basic concept and motivation behind this work before moving on to more complex details.

3.1 Architecture

To solve the generalized HVAC scheduling problem detailed in Section 2.3, this dissertation proposes a novel distributed architecture where heating/cooling is regarded as a service. The provider of the service is the HVAC system and customers are the thermal zones.

Zone modules in each thermal zone maintain local heat transfer models, process user-specified temperature requests, and process available measurements. The zone modules receive forecasts of weather, cooling load, and occupancy. This information, together with the local models are used to compute requests for cooling service over various future windows. These computations are decentralized across zones and

Figure 3.1: Token based scheduling preliminary architecture

reduce to a linear programming problem due to model simplifications. The requests are expressed in terms of the desired amount of cool air, which can be conceptually regarded as *tokens*. The requests may be provided by an AHU by adjusting the damper settings and the fan speeds that regulate the flow of cool air to the thermal zones.

The token requests from various zones may compete, overload the capacity of the system, or result in energy inefficient operation of the HVAC system. A Central Scheduler balances the requests and allocates tokens to each zone for the next time slot. This allocation attempts to minimize the total energy use while respecting operational constraints. It will be shown that this allocation reduces to a quadratic programming problem. Zone modules update their local models based on the measured thermal response from allocated tokens and re-compute forward token requests for subsequent time slots in a Model Predictive Control framework. This proposed token based architecture offers several advantages. The architecture is *scalable* to realistic buildings with 200-500 thermal zones as the computational burden both on

the zone modules and the centralized scheduler is modest. Zone modules naturally deliver *robustness* as local models are adaptively tuned to non-stationary environments, zone requests can accommodate abrupt changes in projected occupancy, and local measurements can serve to detect and localize faults. Finally, the modular nature of the necessary hardware infrastructure implies that deployment costs will be minimal.

3.2 Optimization Problems

The optimization problems solved at both the zone module level and the central scheduler level are described in this section.

3.2.1 Zone Module: Token Requests

Each zone module calculates the cooling energy requirements of its respective zone. These are computed over several forward horizons to get a *cooling energy profile* for each zone. Fix a planning horizon H_p . For each zone i , its associated zone module solves:

$$J_i(H_p) = \min \sum_{k=1}^{H_p} d_r(k) g_i(k) \quad (3.1)$$

subject to

$$\mathbf{C1:} \quad T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 g_i(k) = v_i(k)$$

$$\mathbf{C2:} \quad T_{il}(k) \leq T_i(k) \leq T_{ih}(k)$$

$$\mathbf{C7:} \quad \dot{m}_{il}(k)(T_i(k) - T_c) \leq g_i(k) \leq \dot{m}_{ih}(k)(T_i(k) - T_c)$$

$\forall k : 0 \leq k \leq H_p$. Note that $T_i(k)$ is a linear function of the decision variables $g_i(s)$, $s \leq k$ because the dynamics **C1** are linear. The value of $d_r(k)$ is pre-set

according to ventilation needs and maintained by the mixing chamber of the AHU.

We, therefore, have a Linear Programming problem. This can be solved quickly and in parallel for all zones. $J_i(H_p)$ is interpreted as the minimum cooling energy or *minimum number of tokens* needed by zone i on the planning horizon H_p to meet its local temperature constraints.

To coordinate with the Central Scheduler, the Zone Modules generate token requests into mass flow rate requests. More precisely, fix the planning horizon H_p . Let $g_i^{\text{opt}}(k)$ be the optimal cooling request that solves the linear program (3.1). Using the linear dynamics (C1), the associated optimal temperature profile $T_i^{\text{opt}}(k)$ can be computed. Using (2.3), the corresponding mass flow rate request is:

$$\dot{m}_i^{\text{opt}}(k) = \frac{g_i^{\text{opt}}(k)}{c_p(T_i^{\text{opt}}(k) - T_c)} \quad (\forall k : 0 \leq k \leq H_p) \quad (3.2)$$

and the corresponding minimum number of tokens, i.e., the minimum amount of cool air for a planning horizon H_w required for zone i is computed:

$$S_i(W) = \sum_{k=1}^W \dot{m}_i^{\text{opt}}(k) \quad (\forall W : 1 \leq W \leq H_w) \quad (3.3)$$

which is transmitted to the Central Scheduler using standard IP protocols. It supplies a *lower bound* on the total mass flow of air demanded by zone i on the planning horizon H_p , as dictated by zone thermal dynamics and acceptable temperature ranges.

3.2.2 Central Scheduler: Token Allocation

The Central Scheduler attempts to allocate mass flow rates to all zones while minimizing total energy consumption. In this step zone thermal dynamics and acceptable temperature ranges are discarded, as they are captured by the request

profile $S_i(H_p)$. The Central Scheduler solves the following optimization problem:

$$\min \sum_{k=1}^W \left(\frac{c_p}{\mu_c} \right) (1 - d_r(k)) (T_{oa}(k) - T_c) \sum_{i=1}^{n_z} \dot{m}_i(k) + P_f(k) \quad (3.4)$$

subject to

$$\sum_{k=1}^W \dot{m}_i(k) \geq S_i(W) \quad (\forall W : 1 \leq W \leq H_w) (\forall i : 1 \leq i \leq n_z) \quad (3.5)$$

$$\dot{m}_{il} \leq \dot{m}_i(k) \leq \dot{m}_{ih} \quad (\forall i : 1 \leq i \leq n_z) (\forall k : 1 \leq k \leq W) \quad (3.6)$$

The decision variables are the mass flow rates $\dot{m}_i(k)$. The objective function (see (2.16, 2.13)) is quadratic in the decision variables, and the constraints are linear inequalities. Such a quadratic program can be efficiently solved with standard software tools. In essence, the Central Scheduler tries to low-pass filter the total mass flow rate to reduce operational energy consumption.

3.3 Simulation Study

The token-based scheduling strategy described above is implemented in MATLAB. The setup of the experiments and the corresponding results are described below.

3.3.1 Simulation setup

The simulations were conducted for a synthetic building with five zones. A single AHU serves all five zones, and one centralized chiller supplies chilled water to the AHU cooling coils. The zone service hours and desired temperature set-points are detailed in Table 3.1. The parameter values used for the simulations are listed in Table 3.2. The cooling load profile and the ambient temperature profiles are as shown in Figs. 3.3 and 3.4, and these are identical for all zones. The return air to

Figure 3.2: d_r profile

Figure 3.3: Cooling load profile

Figure 3.4: Ambient temperature profile

total air ratio profile, d_r , is shown in Fig. 3.2.

Table 3.1: Zone thermostat settings for five zones

Zone	Occupied hours		Acceptable temperature range (°C)			
	Start	End	Occupied hours		Unoccupied hours	
			Low	High	Low	High
1	7:00	19:00	21	24	12	32
2	6:00	18:00	21	25	12	32
3	9:00	13:00	20	22	12	32
4	5:00	19:30	21	23	12	32
5	5:00	19:30	21	24	12	32

Table 3.2: Thermal parameters

Parameter	Value	Unit
c_p	1	$\text{kJ}/(\text{kgK})$
c_i	1000	kJ/K
$1/\eta$	4	dimensionless
R_i	0.15	kW/K
k_f	1.675	$\text{kW s}^2/\text{kg}^2$
T_c	12	$^{\circ}\text{C}$
δ	30	minutes
H_p	24	hours
W	2	dimensionless

3.3.2 Simulation results

The simulation results are shown in Fig. 3.5. The temperature profiles reveal that the acceptable temperature ranges are not violated for all zones. The temperature trajectories tend to follow the upper bound of these ranges to expend minimal energy for cooling the zones. The zones are typically pre-cooled 60 minutes in advance of occupancy. Longer pre-cooling requires larger energy consumption in the chiller because of increased net external cooling load, while shorter pre-cooling results in larger air mass flow rates increasing the energy consumption in the fan. The token-based strategy balances these effects to minimize overall energy consumption.

The sensitivity of total energy cost with respect to sampling time and window length W under token based scheduling is shown in Fig. 3.6. Recall that each zone module generates token request constraints over various forward windows up to W hours. Small sampling times result in peaky air mass flow rates, with the fan supplying the bulk of the token requests at the end of the pre-cooling period, and waste energy in the fan unit. Large sampling times result in long pre-cooling periods, and waste energy in the chiller. It can be empirically observed that a sampling time of 20 minutes results in the lowest total energy consumption in our simulation.

Figure 3.5: Simulation Results - Token based scheduling strategy

Figure 3.6: Energy cost Vs. Sampling time

Case 1: Comparison with Centralized Scheduling

We compare results from the token based algorithm with a centralized approach that can be regarded as the ‘optimal’ energy minimizing strategy. The centralized approach combines the temperature demands, weather predictions, fan and chiller power consumption, and occupancy predictions into a single sequential quadratic programming problem. While the results of this approach are compelling for a small number of zones, it fails for a modest number of zones even without including damper, pressure or COP constraints.

Figure 3.7: Centralized Non-linear Optimization results for Case 1

Figure 3.8: Token based scheduling results for Case 1

Six zones with varying service hours and temperature demands are chosen for the simulation. It is evident from Figs. 3.7 and 3.8 that the temperature profile followed by the zones for both strategies are very similar. The dotted lines in the temperature graph represent the preset thermal comfort range for the respective zone. The comparisons for energy consumption and computation times are summarized in Table 3.3. The token-based strategy is suboptimal by $\approx 2\%$. This is

Table 3.3: Comparative results for Case 1

Algorithm	Computation time (seconds)			Energy consumption(kJ)	
	50 zones	120 zones	400 zones	6 zones	15 zones
Token based scheduling	1.70	2.76	6.69	1990.4	5594.9
Centralized non-linear optimization	560	-	-	1950.3	5476.5

negligible compared to the computational advantage gained, and most importantly, the modular simplicity of its architecture. The advantage of its scalability to large buildings becomes evident with a larger number of zones. The centralized approach completely fails to converge for more than 100 zones.

Case 2: Comparison with Legacy Singapore Cooling Strategy

In Singapore, pre-cooling of building spaces begins at a fixed time for all zones before the expected arrival of the first occupants. The mass flow rate of cool air supplied during the pre-cooling period is constant. The pre-cooling period is typically around 30-45 minutes. All zones are pre-cooled at the same time. The zone temperature demands are not handled individually. This strategy was implemented in MATLAB [103] for six zones to compare with the token-based scheduling strategy. For a better comparison, the token-based strategy was implemented for rooms with the same temperature requirements but with varying service times.

Figures 3.9 and 3.10 shows the difference in temperature trajectories between both strategies. The token-based strategy only supplies enough cool air, to satisfy the minimum cooling requirement. The legacy Singapore strategy satisfies the temperature demands, but cool zones that are not even in service. The savings in terms of

Figure 3.9: Legacy Singapore Cooling Strategy results

Figure 3.10: Token based scheduling results for Case 2

energy for the specified setup is 17%. The amount of savings that is expected will depend on the room service hours, the temperature demands, and most importantly, the number of zones under consideration - the more the number of zones, the higher the possible energy saving due to the increasing impact of coordination of cooling services among individual zones. For this reason, it is anticipated that this strategy will save much more energy when dealing with large buildings.

3.4 Summary

This chapter presented an intuitive structure of the proposed token-based scheduling strategy for the reader's understanding. The strategy aims to reduce the energy consumed by the chiller and fan, which are the components that consume the bulk of the energy in HVAC systems. In this version, the strategy deals with the most common constraints seen in HVAC scheduling systems, namely, thermal comfort demands, cool air mass flow rate bounds, zone thermal dynamics, and fan capacity. The scheduling technique is simulated in MATLAB using parameters from existing literature and compared to results from existing centralized techniques, which is considered 'optimal'. The comparison shows that the token-based scheduling strategy is suboptimal by only 2% while there is a significant reduction in com-

putational complexity. This makes the strategy scalable to large buildings while maintaining robustness to uncertainties in load forecasts. The technique also has a low deployment cost while maintaining modular simplicity. In the next chapter, more operational constraints will be included in the strategy, which have not been studied in the current literature in the context of HVAC system scheduling.

Chapter 4

Token Based Scheduling Strategy with Operational Constraints

Chapter 3 explains the basics of the token-based scheduling strategy. For effective scheduling of HVAC services, a number of operational constraints like chiller capacities, duct pressure, damper positions, and chiller COP need to be taken into consideration. These operational constraints make a huge difference to the resulting optimal solution as shown later in this chapter.

The architecture essentially remains the same with zone modules and a central scheduler. The zone modules conduct decentralized computations for calculating token requests, while the central scheduler now has two tasks. The first computation in the central scheduler is to increase the COP efficiency of the chiller while satisfying the token requests put forth by the zone modules. To achieve this, the scheduler checks if an increase in the cooling load will benefit the chiller by solving a mixed integer linear programming problem. The second task of the central scheduler is to optimize for the fan power consumption while satisfying the duct pressure and damper position constraints, which is a quadratic constrained quadratic programming problem. This new architecture is depicted in Fig. 4.1.

Figure 4.1: Token Based Scheduling Strategy Complete Architecture

4.1 Sub-problem 1: Token Requests in Zone Modules

The first sub-problem is called *token requests*, which consists of a cost function of:

$$\sum_{i=1}^{n_z} \left[c_p d_r \sum_{k=0}^{H_p} g_i(k) \delta \right] \quad (4.1)$$

associated with constraints **C1**, **C2** and **C7**. The cost function is part of the chiller energy consumption with the assumption that the chiller COP is 1, i.e., $\eta = 1$ for all $k = 1, \dots, H_p$. Such a choice is made because chiller is the dominant component in terms of energy consumption. The cost function is clearly decomposable with respect to each individual zone, and so are the constraints **C1**, **C2** and **C7**. This nice problem structure leads to a simple physical interpretation, that is, each zone i tries to minimize the total zone energy consumption $\sum_{k=0}^{H_p} c_p d_r g_i(k) \delta$, while satis-

fying its own thermal dynamic constraint and the temperature set-point constraint. Furthermore, the zone modules also consider the chiller capacity constraints given in **C6** using a Lagrangian relaxation algorithm with Lagrangian multiplier λ . At every iteration, the zone module computes the cooling request $g_i(k)$ and transmits it to the central scheduler. Since the constant in the cost function will not affect the optimal solution of $\{g_i(k) | 1 \leq i \leq n_z \wedge 0 \leq k \leq H_p\}$, the constant can be set as 1, and have the following zone level optimization problem for each zone i :

$$J_{1,i}(H_p) = \min_{g_i} \sum_{k=1}^{H_p} \left[d_r(k)g_i(k) + \lambda_k g_i(k) \right] \quad (4.2)$$

subject to

$$\mathbf{C1:} \quad T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 \dot{m}_i(k)(T_i(k) - T_c) = v_i(k) \quad (\forall k : 0 \leq k \leq H_p)$$

$$\mathbf{C2:} \quad T_{il}(k) \leq T_i(k) \leq T_{ih}(k) \quad (\forall k : 0 \leq k \leq H_p)$$

$$\mathbf{C7:} \quad \dot{m}_{il}(k)(T_i(k) - T_c) \leq g_i(k) \leq \dot{m}_{ih}(k)(T_i(k) - T_c) \quad (\forall k : 0 \leq k \leq H_p)$$

The multipliers are updated for each iteration n , as

$$\lambda_k^{n+1} = \max(0, \lambda_k^n + s_k G(\lambda^n))$$

where, gradient $G(\lambda^n(k)) = \sum_i g_i(k) - g_{cap}$, Step size $s_k = \frac{\beta}{\|G(\lambda_k^n)\|_2}$, $\beta > 0$ is a scalar. The optimization is repeated for a fixed number of iterations. Sub-problem 1 consists of n_z such simple linear programming problems solvable efficiently and simultaneously in a distributed manner. From an application point of view, each zone can be associated with a *zone module*, which consists of sensors such as thermostat, occupancy sensors, mass flow rate sensors, and damper position sensors, and a solver for the above optimization problem such as CVX [104]. Such a zone module will undertake zone computation and data-driven model identification, and

parameter forecast. The outcome $\{g_i^*(k) | k = 0, \dots, H_p\}$ of each zone module i will be sent to the next stage in the form of cooling energy tokens, which aims to solve Sub-problem 2, where the actual chiller COP will be taken into account. Given an arbitrary time window size $H_w \leq H_p$, the corresponding token requests associated with a given window size are defined for zone i as follows:

$$TokA_i(W) = \sum_{k=1}^W \dot{g}_i^*(k) \quad (\forall W : 1 \leq W \leq H_w) \quad (4.4)$$

Algorithm 4.1 Sub-problem 1: Computing Token Requests

Input: Forecasts for T_{il} , T_{ih} , $v_i(k)$

Output: $g_i(k)$

Initialisation: $g_i(0), T_i(0), T_{oa}(0)$

for $k = 1 : H_p$ **do**

 Measure $T_i(k)$

 Compute $g_i(k)$ from Eq. (4.2)

end for

Compute $TokA_i(W)$ ($\forall W : 1 \leq W \leq H_w$) from Eq. (4.4)

return $TokA_i$

4.2 Sub-problem 2: Incorporating Chiller COP

In this sub-problem the following cost function is considered:

$$\sum_{k=0}^{H_p} \tilde{P}_c(k) \Delta = \sum_{k=0}^{H_p} c_p \eta(k) \sum_{i=1}^{n_z} g_i(k) \delta, \quad (4.5)$$

where $c_p g_i(k) := c_p \dot{m}_i(k)(T_i(k) - T_c)$ is the cooling load of zone i at k , associated with the constraint **C3** about the reciprocal of COP, $\eta(k)$, and the constraint of

$$(\forall i : 1 \leq i \leq n_z)(\forall k : 0 \leq k \leq H_p) g_i(k) \geq g_i^*(k),$$

where $g_i^*(k) := \dot{m}_i^*(k)(T_i^*(k) - T_c)$ is attainable based on the outcome of Sub-problem 1, which denotes the minimum cooling load of zone i at k . The motivation behind this problem formulation is that, first of all, each zone needs to ensure the minimum cooling load to be removed to comply with the zone set-point, i.e., $g_i(k) \geq g_i^*(k)$; secondly, by taking the actual COP into account, it may save more energy by increasing the zone cool demand (i.e., to increase the cooling load). Although the savings in incorporating COP into the algorithm may not be too large over a small time period like a day or a week, the annual savings is not negligible.

The sub-problem 2 is formally defined as follows:

$$\min J_2(H_p) = \sum_{k=0}^{H_p} \eta(k) \sum_{i=1}^{n_z} g_i(k) \quad (4.6)$$

subject to

$$\mathbf{C3:} \quad (\forall k : 0 \leq k \leq H_p) \quad \eta(k) = \begin{cases} \eta_1 & \text{if } \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch1} \\ \eta_2 & \text{if } Q_{ch1} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch2} \\ \eta_3 & \text{if } Q_{ch2} < \sum_{i=1}^{n_z} g_i(k) \leq Q_{ch3} \\ \vdots & \\ \eta_{n_j} & \text{if } \sum_{i=1}^{n_z} g_i(k) > Q_{ch(n_j-1)} \end{cases}$$

Constraint from Sub-problem 1: $(\forall i : 1 \leq i \leq n_z)(\forall k : 0 \leq k \leq H_p) g_i(k) \geq g_i^*(k)$

Constraint **C3** is a set of mixed logic constraints [105], which, by introducing proper Boolean variables, can be converted into mixed integer linear constraints, and the variable $\eta(k)$ can be written as the sum of those Boolean variables weighted on those η_j ($1 \leq j \leq n_j$), which makes the original cost function become a mixed integer quadratic function. After defining new variables, the mixed integer quadratic programming problem can be reduced to a mixed integer linear programming problem.

To minimize notational complexity, the complex transformation from mixed logic constraints to mixed integer linear constraints is described in Appendix A, where interested readers can obtain more details about this transformation. To solve the mixed integer linear programming problem obtained via the transformation, there are many tools that can be used, e.g., GUROBI or CPLEX. Let the final solution be

$$\{\tilde{g}_i^*(k) | 1 \leq i \leq n_z \wedge 0 \leq k \leq H_p\}.$$

By using the linear thermal dynamics **C1** in each zone i , the associated zone temperature profile $\tilde{T}_i^*(k)$ can be computed, upon which, the corresponding mass flow rate is calculated for zone i :

$$\tilde{m}_i^*(k) = \frac{\tilde{g}_i^*(k)}{c_p(\tilde{T}_i^*(k) - T_c)}$$

The token request associated with the given window size W for zone i is as follows:

$$TokB_i(W) = \sum_{k=1}^W \tilde{m}_i^*(k) \quad (\forall W : 1 \leq W \leq H_w) \quad (4.8)$$

Algorithm 4.2 Sub-problem 2: Incorporating Chiller COP

Input: $TokA_i$ from Algorithm 4.1, $\eta_1 \cdots \eta_{n_j}$

Output: $TokB_i$

for $k = 1 : H_p$ **do**

 Compute $\tilde{g}_i^*(k)$ from Eq. (4.6)

end for

 Compute $TokB_i(W)$ ($\forall W : 1 \leq W \leq H_w$) from Eq. (4.8)

return $TokB_i$

We interpret $TokB_i$ as the *minimum number of tokens* needed by zone i within the

planning window H_w to meet its local temperature constraints within that window. This quantity will be used to replace the zone thermal dynamic model and zone set-point constraint (i.e., Constraints **C1** and **C2**) in Sub-problem 3 with a belief that, as long as it can be ensured that the actual allocated token number in each zone i at each k is not smaller than the minimum one $TokB_i$, the zone set-point will be met.

4.3 Sub-problem 3: Token Allocation

Sub-problem 3 aims to take the energy consumption of the fan into account while complying with the duct pressure distribution constraint **C4** and the fan capacity constraint **C5**. Thus, the following cost function is chosen:

$$\sum_{k=0}^{H_w} P_f(k) \Delta = \sum_{k=0}^{H_w} k_f \left(\sum_{i=1}^{n_z} \dot{m}_i \right)^2, \quad (4.9)$$

where $H_w \leq H_p$ is a pre-chosen time window, in which the fan energy consumption is considered. Optimizing the fan energy consumption will not be considered over the entire scheduling horizon H_p because this will lead to averaging the total cool air supply over H_p due to the quadratic power function of the fan. But a flat accumulative mass flow rate function will lead to substantially high chiller energy consumption, which is certainly undesirable because the chiller energy consumption is the dominant term for the entire HVAC energy consumption. Due to this reason, only a small time window is considered for optimizing the fan energy consumption, i.e., to fine tune the token requests obtained from Sub-problems 1 and 2 by adding the impact of the fan. Although, only a small time window is considered, by adopting the model predictive control strategy, i.e., to look into one small window per each step, eventually the entire service request period will be covered. To avoid considering the zone thermal dynamic constraints explicitly in Sub-problem 3, the

zone mass flow assignment (or the token allocation) for each zone i is enforced to be no smaller than the token request for zone i obtained in Sub-problem 2. We have the following problem formulation:

$$\min J_3(H_w) = \sum_{k=0}^{H_w} \left(\sum_{i=1}^{n_z} \dot{m}_i \right)^2 \quad (4.10)$$

subject to

$$\mathbf{C4-1:} \quad (\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) p_i(k) - p_z = a_i \frac{\dot{m}_i(k)^2}{A_i(k)^{5/2}}$$

$$\mathbf{C4-2:} \quad (\forall i : 1 \leq i \leq n_z - 1) p_{i+1}(k) - p_i(k) + f_i \left(\sum_{q=i+1}^{n_z} \dot{m}_q(k) \right)^2 \leq 0$$

$$\mathbf{Constraint from Sub-problem 2:} \quad (\forall i : 1 \leq i \leq n_z)(\forall W : 0 \leq W \leq H_w)$$

$$\sum_{k=0}^W \dot{m}_i(k) \geq TokB(W)$$

This problem is unfortunately not convex due to the constraint **C4-1**, which is about the cool air delivery through each damper, and is equivalent to the following two inequality constraints:

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) p_i(k) - p_z - a_i \frac{\dot{m}_i^2(k)}{A_i^{5/2}} \leq 0 \quad (4.12a)$$

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) p_i(k) - p_z - a_i \frac{\dot{m}_i^2(k)}{A_i^{5/2}} \geq 0 \quad (4.12b)$$

In reality, the dampers at the entrance of a zone are designed not to completely close at any time. As long as the fan is running, a small amount of cool air enters a zone captured by a non-zero damper opening (2.10). In other words, constraint (4.12a) becomes active when $\dot{m}_i(k)$ is small. In this case, $\dot{m}_i^2(k)$ can be approximated as

$\dot{m}_i(k)$, and replace constraint (4.12a) by the following convex one:

$$(\forall k : 0 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) p_i(k) - p_z - a_i \frac{\dot{m}_i(k)}{\underline{A}_i^{5/2}} \leq 0. \quad (4.13)$$

Constraints (4.13) and (4.12b) are used to replace the constraint **C4-1** in the above sub-problem 3 formulation. A convex quadratic constrained quadratic programming problem is obtained, which can be solved efficiently via some interior point method. Several toolboxes are available, e.g., CPLEX, Gurobi.

Algorithm 4.3 Sub-problem 3: Token Allocation

Input: $TokB(k)$, p_{cap} , $\underline{A}_i$, $\overline{A}_i$

Output: $\dot{m}_i(k)$, $p_i(k)$, $p_0(k)$

for $k = 1 : H_p$ **do**

 Compute $\dot{m}_i(k)$ from Eq. (4.10)

end for

 Send token allocation signal to building management system

4.4 Simulation Study

This section explores scalability of the scheduling strategy and the ease with which system constraints on mass flow rates and chiller coefficient of performance can be incorporated into the token-based scheduling algorithm. Sub-problem 2 deals specifically with incorporating chiller coefficient of performance. Previous research on HVAC scheduling has not systematically addressed this key practical consideration. Most commonly, chiller inefficiencies are dealt with through chiller staging, which determines the combination of available chillers to be used at various times of the day. In this work, the available chillers are fixed, and the cooling loads are modified to minimize energy use by taking into account chiller inefficiencies. Staging can be considered as a higher level decision in a hierarchical control scheme. For the purpose of simulations, due to the approximation of constraint **C4-1** in the formulation

Table 4.1: Thermal parameters

Parameter	Value	Unit
c_p	1	kJ/(kgK)
c_i	1000	kJ/K
R_i	0.15	kW/K
k_f	1.675	kWs ² /kg ²
T_c	12	°C
δ	30	minutes
H_p	24	hours
n_j	7	dimensionless
p_z	800	Pascal
W	2	dimensionless
Initial zone temperature	30	°C

of Sub-problem 3, an extra optimization is carried out after solving Sub-problem 3 for every iteration to calculate the actual mass flow rate profile that is applied to the building duct network.

Figure 4.2: Reciprocal of Coefficient of Performance for Chiller, η

4.4.1 Simulation Setup

The token-based scheduling strategy was implemented in MATLAB [103] R2014a on a PC with Intel Core i7 processor, 8GB RAM, and 64-bit Operating System. The non-convex optimization in Sub-problem 1 was solved by using the MATLAB

Figure 4.3: Results for token based scheduling with operational constraints

Table 4.2: Simulation Results - computation times of token based scheduling for increasing number of zones

Number of zones	Computation time(seconds)
10	1.24
50	1.39
100	12.20
150	50.20

optimization toolbox, and the MILP problem in Sub-problem 2 and the QCQP problem in Sub-problem 3 were solved by IBM ILOG CPLEX for MATLAB toolbox [106]. The parameter setup for the simulations are given in Table 4.1 and Figures 3.3, 3.4, 3.2, and 4.2.

4.4.2 Simulation Results

Figure 4.3 shows the result of implementing the token strategy on six zones with different cooling service hours.

Figure 4.4: COP included in scheduler Figure 4.5: COP excluded from scheduler

The computation times are summarized in Table 4.2 and underscore the computational and scaling benefits of token-based scheduling. The temperature profile does not precisely track the upper bound for two reasons: (1) the effect of chiller COP, and (2) the actual pressure distribution in the ducts.

To evaluate the impact of chiller COP on the total energy saving, Sub-problem 2 is skipped, i.e., assuming $COP=1$ all the time. After applying the solution obtained with the same setup as above, the energy consumption and COP profiles are compared to the above results. Figs. 4.4 and 4.5 show this comparison. It is evident that the inclusion of Sub-problem 2 has considerably changed the COP profile. The energy savings due to inclusion of the COP factor into the token-based scheduling strategy alone is around 1.4% for 5 zones and 17.9% for 100 zones specific to the setup used in the simulations.

4.4.3 Performance under sudden changes in temperature demands

The robustness of the energy savings performance of the token-based scheduling strategy can be studied by changing the comfort bands of the zone. Here, it is assumed that the zone 3 temperature is suddenly changed from 23°C to 25°C at

10 a.m. The strategy adapts fast to this change as evident from Fig. 4.6. The

Figure 4.6: Temperature profile at the time of set-point change and end of day

left-hand side graph shows the scheduled temperature profile at 10:00 a.m. is to be maintained at 25°C for the next few hours. But exactly at 10am, an occupant changes the setting to 23°C. The algorithm tries to incorporate this new demand and pushes in as much air as it would be necessary to attain this new set-point at the earliest. When the temperature profile is observed at the end of the day, it is seen that there was a delay of only one time-step (10 minutes) to decrease the temperature of the zone. The decreased computational complexity of the algorithm over existing approaches can guarantee that any sudden changes in demands are effectively handled as soon as possible.

4.4.4 Performance under sudden cancellation of meeting

The HVAC scheduling strategy could be hooked up to the room scheduling software in a particular office. This would mean that if any conference rooms are booked for a meeting, the HVAC system would be notified of the expected increase in cooling demand and occupancy for the zone at that time.

This case is to explore what happens when a cooling demand for a particular zone is suddenly changed. When a meeting is scheduled in an otherwise empty room, the

Figure 4.7: Temperature profile at the time of meeting cancellation and end of day

activity and occupancy of the room are expected to increase. As this information is already provided to the system in advance, it prepares to deal with this increased cooling load by pumping more cool air. Let us assume that zone 6 is expected to have a sudden increase in occupancy at 11am for one hour and that the set-point for this hour is set to 22°C as shown in the left-hand side of Fig. 4.7. But, exactly at 11am, the meeting is canceled. The algorithm receives this information and tries to save energy by changing this schedule and only pumping in enough air to maintain the 24°C zone temperature. The final temperature profile at the end of the day is shown on the right side of Fig.4.7. It should be observed that cooling starts expecting the increase in demand and stops as soon as the cancellation is conveyed to the HVAC system.

The two performance studies described above show that the fast response to uncertainties by the token-based scheduling strategy is an important advantage that prevents unnecessary cooling and enhances thermal comfort.

4.5 Lower bound estimate

Sub problem 1 of the token based scheduling strategy (TBSS) generates token requests that represent the optimal chiller power consumption profile subject to

thermal comfort constraints and zone dynamics. On the other hand, the centralized strategy computes the mass flow rate profile that optimizes both the chiller and fan energy. In this backdrop, a major concern is whether the token-based solution may lead to a total HVAC energy consumption too far away from the truly optimal one. In other words, how to measure the quality of the solution in terms of its “distance” from the globally optimal one. Since it is practically infeasible to determine the actual globally optimal solution due to the expected prohibitively high computational complexity, to answer the aforementioned question, a specific method is presented to derive a lower bound on the globally optimal HVAC energy consumption. By comparing the difference between the HVAC energy consumption incurred by the token-based solution and this lower bound, it can be approximately calculated whether the solution is sufficiently close to the globally optimal one.

The optimization model in (4.2) has capacity constraints that requires iterative computation of $\lambda(k)$. The optimization model formulated without the capacity constraints is defined as the *Relaxed Token* (RT) $\mathcal{M}_{1,i}$ given by

$$\mathcal{M}_{1,i} := \min_{g_i} \sum_{k=1}^{H_p} g_i(k) \quad (4.14)$$

subject to

$$\begin{aligned} T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 g_i(k) &= v_i(k) & (\forall k : 1 \leq k \leq H_p) \\ T_{il}(k) &\leq T_i(k) \leq T_{ih}(k) & (\forall k : 1 \leq k \leq H_p) \end{aligned}$$

We have the following main theorem.

Theorem 1 Let $\mathcal{P}_1$ and $\mathcal{P}_2$ denote the power consumption for mass flow rate profiles $\{\dot{m}_{1,i}(k) | 1 \leq k \leq H_P\}$ and $\{\dot{m}_{2,i}(k) | 1 \leq k \leq H_P\}$ for zone i , respectively. Then $\mathcal{P}_1 \leq \mathcal{P}_2$ implies that $\sum_k \dot{m}_{1,i}(k) \leq \sum_k \dot{m}_{2,i}(k)$. $\square$

Proof: For each $i \in \{1, 2\}$, consider

$$\mathcal{P}_i := c_p \left((1 - d_r)(T_{oa} - T_c) \sum_{k=1}^{H_p} \dot{m}_i(k) + d_r \sum_{k=1}^{H_p} \dot{m}_i(k)(T_i(k) - T_c) \right)$$

Let $\gamma = c_p((1 - d_r)(T_{oa} - T_c))$. Then substituting from thermal dynamics in **C1** and with a little rearranging,

$$\begin{aligned} \mathcal{P}_i &:= c_p \left([(1 - d_r)(T_{oa} - T_c) - d_r T_c] \sum_{k=1}^{H_p} \dot{m}_i(k) + d_r \sum_{k=1}^{H_p} \dot{m}_i(k) T_i(k) \right) \\ &= \gamma \sum_{k=1}^{H_p} \dot{m}_i(k) + \frac{c_p d_r}{\alpha} \sum_{k=1}^{H_p} [T_i(k+1) - T_i(k) + v(k)] \\ &= \gamma \sum_{k=1}^{H_p} \dot{m}_i(k) + \frac{c_p d_r}{\alpha} \left[T_i(H_p) - T_i(1) + \sum_{k=1}^{H_p} v(k) \right] \end{aligned}$$

where $T_i(1)$ is the initial temperature and $v(k)$ is the disturbance due to unpredictable changes in weather and occupancy, which are assumed known in advance.

If $\mathcal{P}_1 \leq \mathcal{P}_2$, substituting for corresponding mass flow rate profiles,

$$\begin{aligned} &\gamma \sum_{k=1}^{H_p} \dot{m}_{1,i}(k) + \frac{c_p d_r}{\alpha} \left[T_i(H_p) - T_i(1) + \sum_{k=1}^{H_p} v(k) \right] \\ &\leq \gamma \sum_{k=1}^{H_p} \dot{m}_{2,i}(k) + \frac{c_p d_r}{\alpha} \left[T_i(H_p) - T_i(1) + \sum_{k=1}^{H_p} v(k) \right] \\ &\Rightarrow \gamma \sum_{k=1}^{H_p} \dot{m}_{1,i}(k) + \frac{c_p d_r}{\alpha} T_i(H_p) \leq \gamma \sum_{k=1}^{H_p} \dot{m}_{2,i}(k) + \frac{c_p d_r}{\alpha} T_i(H_p) \end{aligned}$$

where $\alpha < 1$ and c_p, d_r, α, γ are constants. Therefore, given the same final temperature $T_i(H_p)$,

$$\sum_{k=1}^{H_p} \dot{m}_{1,i}(k) \leq \sum_{k=1}^{H_p} \dot{m}_{2,i}(k),$$

which concludes the proof of the theorem. ■

Corollary 1: Let $\hat{m}_i(k)$ and $\dot{m}_{CP,i}(k)$ denote the solutions of the RT and the cen-

tralized optimization problem (CP) stated in Section 2.3, respectively. Then we have

$$\sum_{k=1}^{H_p} \hat{m}_i(k) \leq \sum_{k=1}^{H_p} \dot{m}_{CP,i}(k). \quad (4.15)$$

□

Proof: Since $\dot{m}_{CP,i}(k)$ is the solution of the CP, it must also be a solution to the RT, as all constraints in the RT must be satisfied by $\dot{m}_{CP,i}(k)$. Since $\hat{m}_i(k)$ is the optimal solution of the RT, the energy consumption $\mathcal{P}_1$ incurred by $\dot{m}_{CP,i}(k)$ in the RT must be higher than the energy consumption $\mathcal{P}_2$ incurred by $\hat{m}_i(k)$. Thus, by Theorem 1, it is clear that the Corollary is true. ■

Let $\hat{g}_i(k)^*$ denote the optimal cooling energy required for each zone during any time period k working with the RT. The corresponding optimal mass flow rate profile is $\hat{m}_i(k)^*$. The following constraint is inserted in the CP: $\forall i : 1 \leq i \leq n_z$,

$$\sum_{k=1}^{H_p} \dot{m}_i(k) \geq \sum_{k=1}^{H_p} \hat{m}_i(k) \quad (k : 1 \leq k \leq H_p)$$

and denote the revised centralized optimization problem as RCP. By Corollary 1, the optimal energy consumption of the RCP and the optimal energy consumption of the CP are the same, i.e., the newly added constraints, which are essentially derived from solving Sub problem 1 (Section 4.1), does not place any active restriction on the optimal solution of the CP. With this important observation, Sub problem 2 (Section 4.2) is slightly modified by replacing the constraint

$$\sum_{k=0}^W \dot{m}_i(k) \geq TokB(W) \quad (\forall W : 0 \leq W \leq H_w)$$

with a new constraint

$$\sum_{k=1}^{H_p} \dot{m}_i(k) \geq TokB(H_p) = \sum_{k=1}^{H_p} \hat{m}_i(k).$$

Denote this revised formulation as Relaxed Token Based Scheduling Strategy (RTBSS). The following is the statement for the main lower bound result:

Theorem 2: Let $\mathcal{P}_1$ and $\mathcal{P}_2$ be the optimal energy consumptions of the RTBSS and the CP, respectively. Then $\mathcal{P}_1 \leq \mathcal{P}_2$. $\square$

Proof: By the above argument, it is clear that the optimal energy consumption of the RCP is $\mathcal{P}_2$. On the other hand, both Sub-problems 1 and 2 of the RTBSS are sub-problems of the RCP, it is clear that $\mathcal{P}_1 \leq \mathcal{P}_2$. $\blacksquare$

Theorem 2 finally establishes a lower bound estimate of the energy consumption of the original CP. Such a lower bound is obtained by running the RTBSS on the CP. Considering that Sub-problem 2 of the RTBSS is a non-convex QCQP problem, by removing those complex pressure constraints, the problem can be converted into a convex QP problem, which can be solved efficiently. Similarly, constraints in Sub-problem 1 could also be removed. It is not difficult to see that the resulting optimal energy consumption is also a lower bound of the optimal energy consumption of the CP. Nevertheless, the more the number of constraints that are removed, the lower the lower bound, which means the less informative of such a lower bound. Thus, the usefulness of a lower bound and the corresponding computational complexity compete with each other, which is a well-known fact. To illustrate the usefulness of the lower bound estimating strategy, which essentially solves the RTBSS, some experiments are conducted on large scale buildings. To speed up computation, some major operational constraints related to the chiller coefficient of performance, the duct pressures, and the damper positions are removed. Figure 4.8 shows the percentage difference between the optimal energy consumptions of the TBSS and the RTBSS. For cases with more than 250 zones, the difference is more than 16%. On the other hand, the gap between the optimal energy consumptions incurred by CP and the RTBSS is significantly small ($\simeq 0.01\%$ difference) for a building of up

Figure 4.8: Percentage energy consumption difference between original and relaxed strategy vs. number of zones

to 30 zones, larger than which, scalability issues arise for solving CP.

4.6 Summary

This chapter introduces operational constraints into the token-based scheduling strategy for a complete formulation and tests the robustness of the approach to sudden events. The constraints included are chiller capacity, ventilation requirements, duct pressure, damper position and chiller COP selection constraints. The introduction of these constraints does not affect the advantageous hierarchical structure of the algorithm with multiple zone modules and a central scheduler working in coordination for energy savings. To quantify the quality of the HVAC scheduling solution, a lower bound estimation strategy is also presented and experimental data have shown the usefulness of the lower bound estimation strategy. The advantages of the token-based scheduling strategy previously established, namely, scalability to large buildings, low deployment cost, reduced computational complexity, and modular simplicity are maintained in spite of the introduction of these complicated

constraints. In the next chapter, the strategy is validated using the popular building simulation software for more realistic results.

Chapter 5

Online realization of Token Based Scheduling Strategy

EnergyPlus is a popular building simulation software that conducts energy analysis and thermal load simulations. A user inputs a building description from the perspective of the building's physical make-up, associated mechanical systems, etc., and EnergyPlus calculates the heating and cooling loads necessary to maintain thermal control set-points, the energy consumption of primary plant equipment as well as many other simulation details that are necessary to verify that the simulation is performing as the actual building would. Many of the simulation characteristics have been inherited from the legacy programs of BLAST and DOE2 [107].

The token-based scheduling strategy has so far been tested in an open loop manner, using available data in the literature. For more realistic simulations, the zone temperature should be sent back to the controller before making a scheduling decision. The thermal models need to be updated according to more recent weather and zone occupancy data. To test the effectiveness of using this approach in a realistic environment, EnergyPlus is used to validate the approach [108] and close the loop by providing appropriate feedback to the scheduling algorithm. A combination of

Figure 5.1: EnergyPlus building model

three software is used to build the model.

1. Google SketchUp - An open source user-friendly 3D modeling software.
2. OpenStudio - A cross-platform (Windows, Mac, and Linux) collection of software tools to support whole building energy modeling using EnergyPlus.
3. EnergyPlus IDF editor - A whole building energy simulation program used to model both energy consumption and water use in buildings.

First, a commercial building of hundred zones is constructed in Google SketchUp. Then, the HVAC system is constructed in OpenStudio with one chiller and four AHUs, each serving 25 zones. The details of the model setup are given below.

5.1 Building Construction

The open source software Google SketchUp (<http://www.sketchup.com/>) and OpenStudio [109] are used to construct a typical commercial building and set up its HVAC System. SketchUp is a user-friendly 3D modeling software widely used by engineers, designers, architects and builders. In this project, a building of hundred zones was constructed using Google SketchUp shown in Fig. 5.1.

The construction of the building is straightforward with 5 floors containing 20 rooms each. Each room is defined as a separate zone, which employs a hundred thermostats in the building, hence giving, a total of hundred zones. Interior elements such as windows, doors, walls, and roofs are added to the model to simulate a real building to make the results more realistic. A great advantage of SketchUp is that it automatically assigns roof and wall components to the model constructed, which saves users the trouble of assigning each surface one at a time.

OpenStudio plug-in allows users to quickly create geometry needed for EnergyPlus using the popular SketchUp 3D modeling tool. OpenStudio is used to set up HVAC systems for the building constructed. For this project, one chiller serves chilled water to four air handling units (AHUs) serving 25 zones each. Screenshots of the HVAC setup are given in Appendix B.

Openstudio is only used to setup the HVAC system. Settings for schedules, materials, construction, controls, etc. are later input using the EnergyPlus editor as it is more effective for use in this work.

5.2 Parameter setup in EnergyPlus

EnergyPlus requires several parameters to be input using the EnergyPlus IDF Editor. Screen captures of these parameter settings are included in Appendix C for illustration purposes. The main inputs provided for this work are covered in the categories below:

- Schedules - ‘TypeLimits’ specifies the data type and value limits in the schedules defined by the users while ‘Compact’ is where users create their desired schedules. There are three main types of schedules defined in Schedule:Compact, which are (a) zone occupancy schedule that indicates the number of occupants in the zone, (b) room thermostat setpoint schedule that indicates
-

the temperature of the zone, and (c) activity schedule for each zone at any given time.

- **Surface Construction Elements** - This category describes the physical properties and configuration for the building envelope and interior elements such as walls, roofs, floors, windows, doors for the building. Users are to input the material details such as thermal properties and air gap insulation.
 - **Thermal Zones and Surfaces** - This category requires users to select the interior elements for each surface or sub-surface of the model building under the ‘Construction name’ tab of two sections, ‘BuildingSurface:Detailed’ and ‘FenestrationSurface:Detailed’. For a surface, users have a selection choice of wall, floor or roof. As for a sub-surface, the selection choice is either a window or door.
 - **Internal Gains** - The only section required in this category is ‘People’ where the respective zone occupancy schedules, created earlier, are selected for each of the hundred zones.
 - **HVAC Design Objects** - This category is used to define the outdoor air content to be mixed in an HVAC system. Outdoor air plays an important role whereby fresh air is being supplied and brought into the HVAC system, which in turns increases the indoor air quality and dilutes the polluted and stale indoor air. To indicate the outdoor air content, users will need to first create an ‘Outdoor Air’ object in the ‘DesignSpecification:OutdoorAir’ section and later select the ‘Outdoor Air’ object under the ‘Design Specification Outdoor Air Object name’ tab in the ‘Sizing:Zone’ section.
 - **Zone HVAC Controls and Thermostats** - To create a thermostat control setting for each zone in the ‘ZoneControl:Thermostat’ section, temperature setpoints
-

Figure 5.2: Annual energy consumption results in EnergyPlus

for every zone are to be defined in the section ‘ThermostatSetpoint:SingleCooling’, using the previously defined room thermostat setpoint schedules. Singapore’s cooling requirements correspond to the option ‘SingleCooling’ as only cooling is required throughout the year.

- **Output Variables** - In this category, users are able to generate their desired outputs for analysis purposes. Power, temperature and mass flow rate profiles are the important parameters that will be highly used for comparisons and analysis of results.

Figure 5.2 shows the annual energy consumption pattern for chillers and fan for the hundred zone building under consideration. It can be seen that chillers are responsible for the bulk of the energy consumed in Singapore. The chiller to fan energy consumption ratio varies with the country under study. In general, chillers take up 60-90% energy and fans take up 15-30% energy in a commercial building.

Figure 5.3: Online realization of Token Based Scheduling strategy using EnergyPlus

5.3 Model Identification

The procedure for closing the loop in the token algorithm using EnergyPlus data that reflects closely, the actual zone conditions in a building is shown in Fig. 5.3. Data reflecting the actual zone conditions in the building considering the tropical ambient conditions in Singapore are recorded in a database. This data is the input to the model identification block that uses it to build a thermal model for the building. The building thermal model is used within the token-based scheduling strategy to schedule cool air mass flow rate inputs as explained in the previous chapter. The thermal response of the zones to the token allocation is measured and fed into the model identification block for updating the models. The updated models are then used by the algorithm to schedule token allocation for the rest of the day. The energy consumed by the token-based scheduling strategy is compared with the centralized optimization technique to evaluate the energy savings due to the adaptation of the token algorithm. By using historical data, the model parameters are identified for each thermal zone. Identification results for the six zones of a hundred-zone building are shown in Figs. 5.4 and 5.5. Measurements of zone air temperature, zone supply air mass flow rate, cooling load due to surface convection, internal convective heat gain rate, and outside air temperature are used for the identification procedure. Table 5.1 shows the parameters of the candidate zone thermal model in a modified version of **C1** given in Eq. (5.1) for the six zones in the buildings identified from the EnergyPlus data. It can be seen that the models provide a reasonable accuracy

Figure 5.4: System identification results for first three zone thermal models

Figure 5.5: System identification results for last three zone thermal models

and computational simplicity as they are linear in the parameters.

$$T(k+1) = aT(k) + bQ(k) + cg(k) + d(T_{oa}(k) - T(k)) \quad (5.1)$$

Table 5.1: Parameters of building thermal model

Parameters	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6
a	0.9994	0.9994	0.9993	1	0.9994	0.9992
b	0.000569	0.001024	0.0006494	0.0007421	0.0009338	0.0004229
c	-0.000565	-0.001014	-0.0006451	-0.0007431	-0.0009237	-0.0004089
d	0.004706	0.003956	0.003966	0.00874	0.003932	0.001495
MAE	0.0412	0.0552	0.0471	0.0552	0.0547	0.0384
MSE	0.0063	0.0166	0.0091	0.0159	0.0157	0.0046

5.4 Simulation Results

The token-based scheduling strategy was previously implemented in MATLAB and optimal results were analyzed for 10 zones. For more realistic simulations, the proposed token-based scheduling strategy is implemented on a six-zone and a hundred-zone EnergyPlus building models and the results are discussed in this section. The weather data for the day in consideration is shown in Fig. 5.6. The existing centralized sequential quadratic programming approach is also implemented for the two building models.

The token-based scheduling strategy successfully runs for both building models, while the centralized approach fails for the hundred zone building due to its high computational complexity. The resulting temperature profiles for six zones from both techniques are shown in Fig. 5.7. The zone temperature profiles from both results tend to follow the upper thermal comfort set-point to save energy. This trend is similar to the results obtained from MATLAB simulations conducted previously. Furthermore, the power profiles for both strategies are shown in Fig. 5.8. It can

Figure 5.6: Weather data for EnergyPlus simulations obtained from online database

Figure 5.7: Temperature profile - Token Based Scheduling and Centralized strategy

be noted that the power consumption patterns are very close to each other showing that the resulting power consumption profile from the token-based scheduling strategy is very close to that of the centralized approach, which is considered ‘optimal’. Further, a validation of the token-based scheduling strategy is conducted by showing that the token-based scheduling approach is suboptimal by only 2% while the computation time is faster by a factor of 35. The details of the energy consumption and computation times from these two experiments are given in Table 5.2.

Figure 5.8: Power consumption comparison- Token based scheduling and centralized algorithm

Table 5.2: Experimental results for token based scheduling strategy using Energy-Plus

Experiment	Energy Consumption		Computation time(s)	
	Token Strategy	Centralized Strategy	Token Strategy	Centralized Strategy
Six-Zone	157 MJ	154 MJ	17	620
Hundred-Zone	15074 MJ	Scalability issues	255	Scalability issues

5.5 Summary

This chapter used the popular building simulation software EnergyPlus to close the loop in the token-based scheduling strategy. The thermal response to the token allocation was measured and fed into a simple model identification block after every iteration. The thermal models of all the zones in the building model are updated before the algorithm is run for the next iteration. The same building model was used to apply the existing centralized optimization technique for comparison purposes. Results from both strategies were compared and it is seen that the token-based scheduling strategy is only suboptimal by roughly 2% compared to the results of the centralized technique while the computational complexity is reduced by a factor of 35. Due to this reduced complexity, the strategy is also scalable to large commercial buildings with 300+ thermal zones, for which the existing techniques

fail. EnergyPlus building simulation software is designed to simulate actual building performance and the results obtained using this software are considered realistic.

Chapter 6

Token Based Scheduling Strategy with Time-of-Use Pricing and Grid Flexibility Services

Demand for electricity and the cost to generate it vary throughout the day based on both demand and supply availability, most commercial customers pay a uniform rate per unit of electricity used throughout the day. With the development of smart grids and advanced metering systems, electricity utility customers can now monitor real-time electricity usage and utilities can charge different rates at different times of the day based on differences in the cost of service [110] as shown in Fig. 6.1. The two popular pricing schemes are described below.

1. Fixed charges proportional to the actual energy consumed in kWh , denoted by C_{FIX} .
2. Time of Use (ToU) charges that vary depending on the time of the day, denoted by $C_{TOU}(t) \forall t \in \{1, \dots, H_p\}$. This cost increases during peak-demand periods and reduces otherwise.

The fixed and ToU prices are published by the utility in the day-ahead market

Figure 6.1: Time-of-Use Pricing

(DAM). Contracts are made between a seller and a buyer for the delivery of power in the following day, the price is set and the trade is agreed. The ToU costs encourage customers to individually manage their loads by either reducing or shifting their energy consumption from peak hours to less congested hours. Singapore has not implemented these ToU based electricity rates for its commercial and residential buildings.

Time-based pricing structures are adopted for two related reasons [111]. The first is that time-based pricing can be used to help manage peak demand. The second is that it discourages consumers from using energy at times when costs are higher. Energy market prices are setup in such a way as to encourage electricity usage during off-peak periods. Therefore, the scheduling of HVAC services in commercial buildings must take the energy prices into consideration while allocating cooling services. In addition to energy savings, energy cost savings become an additional objective of the HVAC scheduling system. Section 6.2 of this chapter presents the token-based scheduling algorithm incorporated with Time-of-Use pricing schemes.

One of the major problems faced by electricity providers is the balancing of gen-

eration and load. A deviation in supply-demand balance causes instability of the grid and to prevent this, “ancillary services” are used. The United States Federal Energy Regulatory Commission (FERC) defines the ancillary services as: “those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operation of the interconnected transmission system”. Large commercial buildings are equipped with Building Energy Management Systems (BEMS) which provide an opportunity for communication with the electric grid. Building thermal storage can be used to provide flexibility services to the grid by manipulating the energy consumed by the building HVAC system.

Section 6.3 of this chapter presents an investigation that aims to develop a contractual framework wherein a user defines the flexibility timings within the contracting period. As a result, the aggregator chooses slots suggested by the building for selecting the flexibility. This investigation extends the contract based framework to allow the inclusion of temporal constraints and flexibility in smaller time frames into the contracts from individual zones. Furthermore, a building user defines the flexibility timings rather than the aggregator. In this chapter, the aim of the algorithm is to save energy costs in addition to reducing energy consumption.

6.1 General Building cost savings problem

The general energy cost savings problem is a centralized non-linear optimization problem that minimizes the product of energy costs and energy consumption of fan and chiller.

$$\min \sum_{k=0}^{H_p} (C_{FIX} + C_{TOU}(k))(P_c(k) + P_f(k)) \quad (6.1)$$

subject to **C1**, **C2**, **C3**, and **C5**.

The zone thermal models and comfort margins are handled by the zone controllers

reducing the computation complexity significantly. Further, as only tokens need to be exchanged between the local controller and the central scheduler, communication among various zone sensors and the central controller is also avoided. As a result, the system complexity reduces as a whole, leading to a significant cost reduction.

6.2 Token Based Scheduling Strategy for Energy Cost Savings

The token based scheduling strategy is modified to incorporate energy costs. The objective now changes to reducing the energy cost of operating HVAC chiller and fans while satisfying thermal comfort demands. The electricity provider imposes Time-of-Use prices to encourage users to consume electricity at off-peak hours and this is taken advantage of in the scheduling strategy. The consumers can reduce energy costs while the service provider benefits from reduced peak demand.

6.2.1 Zone Module: Token Requests

The inputs to the zone module are energy costs, measurements on temperature and occupancy from the individual zones, weather predictions from the web, and forecast on cooling load (from energy plus simulations). The zone module optimizes for the energy cost of each zone considering the underlying thermal dynamics, physical, and operating constraints as follows:

$$\min J_{P,1,i} := \sum_{k=0}^{H_p} [C_{FIX} + C_{TOU}(k)] J_{1,i}(k) \quad (6.2)$$

subject to constraints **C1**, **C2** and **C7** for every zone i , where $J_{1,i}(k)$ is defined in Eq. (4.2) of Section 4.1. The outcome $\{\dot{g}_i^*(k) | \forall k : 1 \leq k \leq H_p\}$ of each zone module i is the thermal energy supply vector and will be sent to the next stage in the form

of token requests defined as

$$Tok_{PR,i}(W) = \sum_{k=1}^W \dot{g}_i^*(k) \quad (\forall W : 1 \leq W \leq H_w) \quad (6.3)$$

6.2.2 Central Scheduler

The Central Scheduler runs the same optimization algorithms as proposed in Chapter 4. It first solves a mixed integer linear programming problem, which is the same as Sub-problem 2 in Section 4.2 to improve COP of chillers (**C4**) while using token requests from Eq. (6.3) as a lower bound on the supply air mass flow rate and calculates token requests in terms of air flows to be used in the next and final step. The final step uses these tokens as a lower bound on the total zone air supply and optimizes for the fan energy consumption while satisfying damper position, duct pressure and fan capacity constraints (**C4** and **C5**) same as Sub-problem 2 in Section 4.3.

The solution of the final step is implemented by the respective AHUs in terms of air flow in the duct network. The thermal response to the cool air supply is measured by zone modules before running the first step of the algorithm for the next time horizon. This entire process happens in a model predictive control framework. A simulation study of this formulation is presented in Section 6.4

Algorithm 6.1 Computing Token Requests for Energy Cost Savings

Input: Forecasts for T_{il} , T_{ih} , $v_i(k)$, $C_{TOU}(k)$

Output: $g_i(k)$

Initialisation: $g_i(0), T_i(0), T_{oa}(0)$

for $k = 1 : H_p$ **do**

 Measure $T_i(k)$

 Compute $g_i(k)$ from Eq. (4.2)

end for

 Compute $Tok_{PR,i}(W)$ ($\forall W : 1 \leq W \leq H_w$) from Eq. (6.2)

return $Tok_{PR,i}$

6.3 Grid Flexibility Services in Token-Based Scheduling Strategy

Consumer participation in flexibility programs requires that user preferences be integrated into the contract. The user preferences can be specified as time slots where the building provides flexibility to the grid. Such contracts can also be used to schedule different zones within a building to provide flexibility at different instants.

For using the thermal flexibility in the building during periods with increased energy consumptions, the total thermal input has to be changed from the optimal value by providing incentives. To do this, the utility negotiates a contract for the duration for which the flexibility is required in terms of length of contract period H^c . Typical values of H^c varies from one hour to six hours. The utility also announces the rewards $\overline{\mathcal{R}}(k)$ and $\underline{\mathcal{R}}(k)$, which are the time varying rewards for the upward and downward flexibilities, respectively. They are provided in the real-time market and modulated by the utility based on the grid conditions.

The aggregator receives this signal from the utility and sends the flexibility requests to the BEMS which conveys this information to the zones. The individual zones, then send their flexibility offers and the time preferences for providing it to the BEMS. The flexibility offered can be expressed in terms of temperature, making it easier for occupants to understand the consequences of offering flexibility on the zone. Temporal constraints are required to model the user preferences for providing the flexibility. The flexibility provided by the building can be modeled as

$$(\forall i : 1 \leq i \leq n_z) \quad U_i = n_c \delta \quad (6.4)$$

where n_c is an integer set by the user. Equation (6.4) gives the total amount of time U_i committed by the zones towards flexibility. In addition, the zones also provide

Figure 6.2: Flow of information for providing Grid Flexibility Services

the start and end time of when they are willing to provide flexibility b_i and e_i .

$$\begin{aligned}
 b_i &\geq 1 \\
 b_i + 1 &\leq e_i \\
 e_i - b_i &\leq H^c
 \end{aligned} \tag{6.5}$$

The BEMS decides the time slots that the flexibility can be used and this information is decoded using the status vector for each zone.

$$(\forall i : 1 \leq i \leq n_z) \quad I_i = [I_i(1) \cdots I_i(n)] \tag{6.6}$$

To restrict the number of slots of the flexibility to lie within the allowable time

interval of the contracting period, we have

$$(\forall i : 1 \leq i \leq n_z) \quad \sum_{h=b_i}^{e_i} I_i(h) = U_i \quad (6.7)$$

Dispersed flexibility slots are discouraged and hence, to offer flexibility in successive time slots we have an additional constraint modeled as in [112].

$$(\forall k \leq H_c\delta - U_i + 1)(\forall i : 1 \leq i \leq n_z) \quad \sum_{l=k}^{k+U_i-1} I_i(l) \geq U_i y_i(k) \quad (6.8)$$

where $y_i(k)$ is the binary indicator that indicates that the zone i is offering flexibility and considering $z_i(k)$ to be the indicator for stopping flexibility. The flexibility status information can be defined as:

$$(\forall k : 1 \leq k \leq H_p)(\forall i : 1 \leq i \leq n_z) \quad y_i(k) - z_i(k) = I_i(k) - I_i(k-1), \quad (6.9)$$

It is obvious that:

$$(\forall k \leq H_c\delta - U_i + 1)(\forall i : 1 \leq i \leq n_z) \quad y_i(k) + z_i(k) \leq 1 \quad (6.10)$$

These flexibility constraints are included in the first step of the token based scheduling strategy. The individual zone i solves the following optimization problem in a receding horizon manner to inform the BEMS about the flexibility that can be offered during different time slots in the contracting period.

Zone Module: Token Requests with Grid Flexibility Services

The Zone module optimizes for energy costs and thermal comfort of the zone while maximizing rewards that the zone can obtain by providing flexibility services to the grid.

Every zone i solves the following optimization problem for a prediction horizon H_p :

$$\min \sum_{k=1}^{H_p} \left[C_{FIX} + C_{TOU}(k) \right] J_{1,i}(k) - \overline{\mathcal{R}}(k)\overline{\phi}(k) - \underline{\mathcal{R}}(k)\underline{\phi}(k) \quad (6.11)$$

subject to

C1: Zone thermal dynamics

$$(\forall k : 1 \leq k \leq H_p) \quad T_i(k+1) + \alpha_1 T_i(k) + \alpha_2 g_i(k) = v_i(k)$$

C2: Thermal constraints:

$$(\forall k : 1 \leq k \leq H_p) \quad T_{il}(k) - \underline{\phi}(k) \leq T_i(k) \leq T_{ih}(k) + \overline{\phi}(k)$$

C7: Zone capacity

$$(\forall k : 1 \leq k \leq H_p) \quad \dot{m}_{il}(k)(T_i(k) - T_c) \leq g_i(k) \leq \dot{m}_{ih}(k)(T_i(k) - T_c)$$

C8: Number of slots limit

$$\sum_{k=b_i}^{e_i} I_i(k) = U_i$$

C9: Consecutive slots:

$$(\forall k \leq H_c \delta - U_i + 1) \quad \sum_{l=k}^{k+U_i-1} I_i(l) \geq U_i y_i(k)$$

C10: Flexibility status

$$(\forall k : 1 \leq k \leq H_p) \quad y_i(k) - z_i(k) = I_i(k) - I_i(k-1)$$

C11: Binary indicator constraint

$$(\forall k : 1 \leq k \leq H_p) \quad y_i(k) + z_i(k) \leq 1$$

where $\overline{\phi}, \underline{\phi}, b_i, e_i, U_i$ are provided by users. The above is solved by mixed integer linear programming to get an optimal cooling energy profile $g_{i,GS}^*$. The token requests are calculated as:

$$Tok_{GS,i}(W) = \sum_{k=1}^W \dot{g}_{i,GS}^*(k) \quad (\forall W : 1 \leq W \leq H_w) \quad (6.12)$$

At the Central Scheduler, the flexibility offers from individual zones are bundled by the BEMS and the flexibility is computed for different time instants within the contracting period H_c . The BEMS then sends this information to the aggregator which sends the flexibility bids to the real-time market. The flow of information taking place in this process is shown in Fig. 6.2. The token requests are sent to the Central scheduler for computation of Sub-problems 2 and 3. After the end of the flexibility period, the zone i starts executing the scheduled contract until the next flexibility signal is received.

6.4 Simulation Results

6.4.1 Token Based Scheduling for Energy Cost Savings

To illustrate the performance of the controller with Time-of-Use pricing, energy prices are setup for a day with a peak-demand period between 06 : 00 hours and 16 : 00 hours. The peak-load pricing is quite high compared to normal days and the zone thermal demands, occupancy, cooling load, and weather forecasts are known. The results are shown in figures below. The results are compared to that of the centralized technique and the default thermostat control available through Energy-Plus. The temperature profiles from the token strategy and centralized techniques are shown in Fig. 6.3. Similar trends can be seen in both cases, where the zones are pre-cooled by the zone controller before the peak-load period sensing an increase in energy pricing. The cooling is completely absent at the start of the peak-periods and the zones heat up differently due to different cooling loads as seen in the corresponding mass flow rate profiles shown in Fig. 6.4. The cooling system kicks off again only when the zones reach the upper temperature comfort bound. This trend is true for both the token based and centralized strategies.

A comparison between the power consumption profiles of the token strategy, cen-

Figure 6.3: Temperature profile - Token-Based Strategy and Centralized strategy with Time-of-Use Pricing

Figure 6.4: Total cool air mass flow rate supply profile - Token-Based Strategy and Centralized strategy with Time-of-Use Pricing

tralized optimization, and the default thermostat control are provided in Fig. 6.5. It can be seen that during the peak-load period (14:30-15:30 hours), the peak demand in energy reduces from 11.76 kW to 6.84 kW for the token-based strategy, indicating a 30% reduction in energy peak.

For the centralized technique, such a reduced peak is not obtained. On the contrary the peak increases in an effort to reduce energy consumption during peak rate cost periods. The token based scheduling strategy is more effective in this effect because the central scheduler optimizes for the power consumption of the fan, which does not favor peaks in the total cool air mass flow rate, which results in peaks in energy consumption. However, the average area under the power curve is least for

Figure 6.5: Power consumption profile comparison

Table 6.1: Global Optimization vs. Token-based Scheduling vs. Thermostat control - Energy cost, computational complexity, and peak demand comparison

Algorithm	Computation time (s)	Energy Cost (\$)	Peak Demand (W)
Global optimization	43	51428	11758
Token based scheduling	.13	52864	6804
Thermostat Control	-	57783	9741

the centralized technique among the three strategies but comparatively, the solution from the token-based scheduling strategy is only suboptimal by 2.7%. A comparison of the power consumption profiles of the token-based scheduling strategy, the centralized technique with the default thermostat control is presented in Fig. 6.5. As for the cost, a reduction of about 8.5% is observed due to the token-based strategy as compared to thermostat control. The advantage of using the token-based strategy becomes further evident when the computation times are compared in Table. 6.1.

6.4.2 Providing Grid Flexibility Services

This section presents a preliminary investigation of the application of the proposed flexibility approach to a building consisting of 50 zones. The zone models

Table 6.2: Simulation Parameters

Simulation Parameters	Values
τ	15 min
n_z	50
t_{cs}	8:00 a.m.
t_{ce}	19:00 p.m.
U_{11}	4
b_{11}	5 a.m.
e_{11}	9:00 a.m.

are obtained using conventional system identification techniques on building data. It is important to emphasize here that the simulations are only meant for illustrating the important features of the proposed contract. Two sets of simulations are performed: 1) with a nominal MPC strategy, and 2) with the proposed flexibility approach. The example under consideration uses a control horizon of 24 hours and a scheduling interval of $\delta = 15$ min. The contracting period used in the simulations is $H^c = 11$ hours. The simulation parameters used are shown in Table. 6.2. The electricity tariffs were taken from Singapore power website [113]. It consists of two parts: fixed energy charges and time-of-use charges. The contract problem for 50 zones was solved in MATLAB. For an illustration, the results obtained for zone 11 are presented which show the user preferences, temperature profiles and energy consumption of the particular zone. Next, the overall performance of the contract is illustrated.

Temperature evolutions and the control inputs for zone 11 along with user preferences and the per-unit energy rate, upward and downward flexibility rewards are shown in Fig. 6.6. The user defines four slots of upper flexibility i.e. $U_{11} = 4$, with $b_{11} = 5$ a.m. and $e_{11} = 9$ a.m. Furthermore, the user defines that the flexibility be offered in consecutive time slots. It can be seen that the algorithm schedules exactly four time-slots in the period. Furthermore, in this set of simulations the

Figure 6.6: Zone 11: Temperature, Cooling energy supplied, and energy cost

Figure 6.7: Comparison of Building Energy Consumption

temperature bounds are specified and are allowed not to vary beyond the flexibility limits. The temperature profiles show that the comfort bands are not violated. The cooling energy supplied to the individual zones under temporal constraints is shown in Fig. 6.8. From this result, the use of user-defined flexibility in different time slots is established. The power consumption with the proposed approach applied to the entire zone with a nominal MPC strategy is shown in Fig. 6.7. It was observed over several simulations that there is cost saving of 13.5% in comparison to the nominal MPC strategy.

The temperature profiles and corresponding air supply mass flow rates in the 50 zones of the building are shown in Fig. 6.8. It can be observed that there are no significant violations from the comfort margins even during periods where flexibility is provided to the grid from the building.

6.5 Summary

This chapter uses the proposed token-based scheduling strategy for peak demand reduction and shifting and energy cost savings while reducing energy consumption as opposed to the previous objective of energy savings alone. Fixed and Time-of-Use

Figure 6.8: Mass flow rate and Temperature Profiles for a fifty-zone Buildings

prices are incorporated into the scheduling algorithm for cost savings. The energy savings obtained from the token-based scheduling strategy is comparable to that from the existing centralized techniques. Furthermore, a peak demand reduction of 30% is obtained, which is not directly possible through the existing centralized techniques. This chapter has also presented a method to use flexibility in buildings towards the energy grid ancillary services. The proposed approach is based on contracts and incorporates the timing preferences provided by the user within the contract. The performance of this strategy has been illustrated by simulations on a multi-zone HVAC system, and relevant comparisons with the nominal model predictive control strategy are made. The hierarchical architecture of the strategy is maintained along with its advantages with scalability, robustness, and the low deployment cost.

Chapter 7

Conclusion and Future work

7.1 Conclusion

Electricity is the most widely used form of energy and its global demand is increasing incessantly. However, generation of electricity is the largest source of carbon dioxide emissions and requires significant control measures to mitigate the consequences of climate change. To satisfy its ever-growing demand and reduce its negative effects on the climate, new sustainable technologies are being developed for the replacement of fossil fuels as a source of energy.

The smart grid allows newer sustainable technologies such as wind, solar, and hydroelectric energy sources as well as electric vehicles to be integrated with the current transmission and distribution system. More importantly, smart grids can detect and react to local usage changes as it allows two-way communication between utilities and consumers. Furthermore, it allows for improved security, reduced peak demand, and better power quality. A brief overall structure of a smart grid is shown in Fig. 7.1. This thesis deals with one of the most adaptable components of a smart grid i.e. commercial buildings.

The HVAC systems are the major energy consumers in a commercial building.

Figure 7.1: Typical schematic of a smart grid

The typical characteristic of commercial buildings is that the occupancy, human activity, equipment usage, and thermal comfort demand trends can be easily forecasted as its usage tends to follow a pattern. For example, an office has a five day week with Saturdays and Sundays off. This means that the HVAC needs of the office would be minimal during these two days. Similarly, it is safe to assume that the employees of the office follow a fixed work hour pattern and have similar thermal comfort requirements every work day. This characteristic is used in HVAC scheduling techniques to realize energy and energy cost savings.

The token-based scheduling strategy presented in this thesis offers a novel approach to ensure energy efficient operations for HVAC systems in commercial buildings. The aim is to reduce energy consumed by chiller and fans while maintaining thermal comfort in all zones of the building. The strategy incorporates operational constraints like damper positions, chiller COP, and duct pressure distributions, which have been largely ignored in existing methods for in-building HVAC

optimization. The ventilation constraints of the optimization model capture the effect of fresh air infusion considering room-size and occupancy.

The method has a hierarchical architecture with numerous zone controllers and a central scheduler. The zone controllers use disturbance forecasts to compute the minimum cooling energy required using predictions on the cooling load, ambient temperature, and heating due to occupancy. The cooling requests (called tokens) are transmitted to the central scheduler. Constraints modeling duct pressures, damper positions, ventilation requirements, the chiller coefficient of performance, and capacity are included in the central scheduler to minimize the fan power consumption. To quantify the quality of the HVAC scheduling solution obtained from the token-based approach, a lower bound estimation strategy is also presented.

The most compelling advantages of the token-based scheduling strategy are derived from: (a) its scalability to realistically large commercial buildings, (b) its robustness to occupancy or cooling load changes, and (c) most importantly, its low deployment cost. Small-scale simulation examples reveal the promise of the token-based scheduling strategy. Considerable energy savings are realized over the legacy Singapore pre-cooling strategies. The total energy consumption is only 1-2% larger than the benchmark under centralized nonlinear scheduling, while the computation time is significantly smaller. Simulation studies have shown that the optimality loss with the token strategy is very modest (as compared with purely centralized scheduling).

Further, a validation of the strategy is conducted in the building simulation software EnergyPlus and a model identification block is included to conduct closed loop simulations. The scheduling strategy is also extended towards energy cost savings, where electricity prices that vary with the time of day are taken advantage of. The service provider publishes these Time-of-Use prices and the building management system schedules the HVAC services while optimizing for energy costs, which also

helps in reducing peak energy demands of the building.

The proposed methodology could achieve up to 35% of energy savings for large commercial buildings by using it to replace current practices followed by the HVAC industry in Singapore. This is a significant amount considering that buildings take up almost half of the energy produced in the country.

The Singapore government has proposed to make 80% of the buildings more energy efficient by 2030. Implementing an efficient low-cost scheduling algorithm will save a lot of energy in a particular time in history when we are concentrating so much on climate change and energy conservation.

7.2 Future work

- This dissertation uses a simple linear thermal model for the scheduling strategy. A simple parameter estimation is conducted using data obtained from EnergyPlus but model adaptation has not been addressed. However, when the strategy is put to use in a real building, the zone modules should be able to adapt its parameters according to data available through weather forecasts and measurements from various sensors like thermostats and occupancy sensors. The local thermal model adaptation needs to be robust to uncertainties in occupant activities and weather allowing for more optimal energy savings by the token-based scheduling strategy.
 - Fault detection is another capability that can be incorporated into this strategy. The robust thermal models and fast computations can detect any unusual behavior in the HVAC system which can be used to facilitate subsequent fault isolation in the building.
 - The token-based scheduling strategy can also be modified to incorporate trans-active control, which exploits the thermal storage property of zones by the prior
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planning of HVAC operations. Using decentralized approaches at the token request level, the individual zones can compute flexibility contracts, which simplifies the computation to a great extent compared to centralized approaches. Furthermore, only zones providing flexibility need to perform computations in a multi-zone building at any given time instant.

- In the hardware context, designing, and testing inexpensive prototypes for Zone Modules is underway. For example, the current prototype of each zone module costs about \$185 USD, which includes a BeagleBone Black microprocessor (for solving Sub-problem 1), sensors for temperature, humidity, light, pressure, CO₂ concentration, and a wireless/Bluetooth communication module. The intention is to bring the cost to \$25 USD per module during the stage of mass production. Interface issues with existing building management systems to actuate dampers and sense air quality need to be explored.

Author's Publications

1. Nikitha Radhakrishnan, Seshadhri Srinivasan, Rong Su, Kameshwar Poolla, “Learning Based Hierarchical Distributed HVAC Scheduling with Operational Constraints”, Control Systems Technology, *Manuscript under review*.
2. Nikitha Radhakrishnan, Yang Su, Rong Su, Kameshwar Poolla, “Token based scheduling for energy management in building HVAC systems”, Applied Energy, Volume 173, 1 July 2016, Pages 67-79.
3. Nikitha Radhakrishnan, Yang Su, Rong Su, Kameshwar Poolla, “Token based scheduling of HVAC Services in commercial buildings,” in American Control Conference (ACC), 2015, pp. 262-269, 1-3 July 2015.
4. Nikitha Radhakrishnan, Rong Su, Kameshwar Poolla, “Optimal scheduling of HVAC operations with non-preemptive air distributions for precooling,” in American Control Conference (ACC), 2014, pp. 2253-2260, 4-6 June 2014.

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Appendices

Appendix A

Conversion of COP constraints to mixed integer linear constraints

Bemporad and Morari in [105] proposed a framework for modeling mixed logical dynamical systems, which can be transformed into linear dynamic equations subject to linear inequalities involving real and integer variables. We apply this framework [105] to introduce boolean variables $\delta_j(k) \in \{0, 1\}$ as follows:

$$\delta_j(k) = 1 \iff \sum_{i=1}^{n_z} g_i(k) \leq Q_{chj} \quad \forall j, k \quad (\text{A.1})$$

where $j \in \{1, 2, \dots, n_j\}$. These logical conditions can be rewritten as mixed integer linear inequalities using methods described in [105] as:

$$(u_j - \epsilon)\delta_j(k) + \epsilon \leq \sum_{i=1}^{n_z} g_i(k) - Q_{chj} \leq U_j(1 - \delta_j(k)) \quad \forall k, j = 1, 2, \dots, n_j - 1 \quad (\text{A.2})$$

where $U_j(k) = \max \sum_i g_i(k) - Q_{chj}$, $u_j(k) = \min \sum_i g_i(k) - Q_{chj}$ and ϵ is a small tolerance beyond which the constraint is considered violated. The chiller power

equation in (2.16) with $d_r = 1$ then becomes:

$$\begin{aligned} P_c(k) = & \delta_1(k)c_p\eta_1 \sum_{i=1}^{n_z} g_i(k) + (\delta_2(k) - \delta_1(k))c_p\eta_2 \sum_{i=1}^{n_z} g_i(k) + (\delta_3(k) - \delta_2(k))c_p\eta_3 \sum_i g_i(k) \\ & + (\delta_4(k) - \delta_3(k))c_p\eta_4 \sum_{i=1}^{n_z} g_i(k) + \cdots + (1 - \delta_{(n_j-1)}(k))c_p\eta_{n_j} \sum_{i=1}^{n_z} g_i(k). \end{aligned} \quad (\text{A.3})$$

For any Boolean variable δ and any function $f(x)$, let $\max_x f(x) = U$ and $\min_x f(x) = u$. Then $\delta f(x)$ can be equivalently replaced by an auxiliary real variable $y(x)$, which satisfies the following constraints:

$$\begin{aligned} y(x) &\leq U\delta \\ y(x) &\geq u\delta \\ y(x) &\leq f(x) - u(1 - \delta) \\ y(x) &\geq f(x) - U(1 - \delta) \end{aligned} \quad (\text{A.4})$$

By using this replacement scheme, let $U_j := \max_{k=0}^{H_p} \eta_j c_p \sum_{i=1}^{n_z} g_i(k)$, and $u_j := \min_{k=0}^{H_p} \eta_j c_p \sum_{i=1}^{n_z} g_i(k)$. We introduction the following auxiliary variables:

$$(\forall j : 1 \leq j \leq n_j - 1)(\forall k : 0 \leq k \leq H_p) D_j(k) := \delta_j(k)\eta_j c_p \sum_{i=1}^{n_z} g_i(k),$$

where $D_j(k)$ satisfies the following constraints:

$$\begin{aligned} D_j(k) &\leq U_j \delta_j(k) \\ D_j(k) &\geq u_j \delta_j(k) \\ D_j(k) &\leq \eta_j c_p \sum_{i=1}^{n_z} g_i(k) - u_j(1 - \delta_j(k)) \\ D_j(k) &\geq \eta_j c_p \sum_{i=1}^{n_z} g_i(k) - U_j(1 - \delta_j(k)) \end{aligned} \quad (\text{A.5})$$

Eq. (A.3) is equivalent to:

$$P_c(k) = D_1(k) + \sum_{j=2}^{n_j-1} (D_j(k) - \frac{\eta_j}{\eta_{j-1}} D_{j-1}(k)) + c_p \eta_{n_j} \sum_{i=1}^{n_z} g_i(k) - \frac{\eta_{n_j}}{\eta_{n_j-1}} D_{n_j-1},$$

which is clearly a linear function. Thus we have a problem with a linear cost function and mixed integer linear constraints, i.e., we have a MILP problem.

Appendix B

Illustration of Openstudio settings

OpenStudio is a cross-platform collection of software tools to support building energy modeling using EnergyPlus. It uses a graphical interface and is an open-source project available for download at <https://www.openstudio.net>.

The software provides features to setup loads, schedules and HVAC. For the purpose of the work in this thesis, only the HVAC system is setup through OpenStudio. The version used is 1.7 which works in tandem with EnergyPlus version 8.2.

This chapter provides a detailed explanation of the OpenStudio setup for the hundred zone building used for experiments in this thesis. Screenshots of the OpenStudio (Version 1.7) software are provided for better understanding of the reader.

The equipments used are given in Fig. B.1 and the following are the components setup through OpenStudio:

1. Condenser - The condenser consists of a cooling tower that cools water incoming from the chiller to a pre-set temperature of $4^{\circ} - 7^{\circ}C$ and sends it back to the chiller. Figure B.2 shows the connection of the cooling tower to the chiller with required pumps.
2. Chiller - The chiller receives chilled water from the condenser and supplies it to AHUs for cooling of supply air. In this project, four AHUs are used, which

HVAC component	Symbol
Cooling Tower
Chiller
Cooling Coil
Supply Fan
Adiabatic Pipe
Variable Speed Pump
Thermal Zone
VAV terminal

Figure B.1: OpenStudio symbols

Figure B.2: Condenser setup

are all supplied chilled water from one chiller. Figure B.3 shows the connection of the chiller to the cooling coils of the AHUs with required pumps.

3. Air Handling Unit - The supply air is cooled in the AHU and supplied to the zones in its network. Each AHU supplies air to 25 zones. Figure B.4 shows the setup of a sample AHU at the supply side with the cooling coils and the supply fan while Fig. B.5 shows its connections to multiple zones. Each zone is fitted with a VAV unit for control of air volume rate into the zone.

Figure B.3: Chiller setup

Figure B.4: Sample AHU setup: supply side

Figure B.5: Sample AHU overall setup

Appendix C

Illustration of EnergyPlus settings

This chapter explains the setup of EnergyPlus parameters for a hundred zone building that was used for simulations in chapter 5. The EP-Launch interface is used to run EnergyPlus .idf files. The IDF editor provides a spreadsheet-like environment to input data, while EP-Launch displays errors and warnings at the end of each run. EP-Launch also acts as a file manager through which users can access data about available input and output parameters, spreadsheet of results, and detailed error files.

The following list provides a brief description of the most important objects that are setup for experiments along with supporting screenshots.

- Schedule Type - They represent the data type of schedules setup by the user. For example, temperature is continuous while occupancy is input as fractions (Fig. C.1).
- Schedule - This allows the user to schedule various parameters like occupancy, thermostat, occupant activity, lighting, etc (Fig. C.2).
- Material - This object requires the materials used in the building to be specified. Various thermal properties of the materials, like conductivity, density,

Figure C.1: Schedule data type object setup

Figure C.2: Schedule object settings

Class List

Schedules

- [0006] ScheduleTypeLimits
- [-----] Schedule:Day:Hourly
- [0036] Schedule:Day:Interval
- [-----] Schedule:Day:List
- [0012] Schedule:Week:Daily
- [-----] Schedule:Week:Compact
- [0012] Schedule:Year
- [0202] Schedule:Compact
- [0002] Schedule:Constant
- [-----] Schedule:File

Surface Construction Elements

- [0003] Material
- [-----] Material:NoMass

Comments from IDF

Explanation of Object and Current Field

Object Description: Regular materials described with full set of thermal properties

Field Description:
ID: A1
Enter a alphanumeric value
This field is required.

Field	Units	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	Obj7
Name		Heavy Weight Conc	Slate Roofing Tile	Ceramic Floor Tile	Plaster Ceiling Tile	Gypsum Board	Insulation Board	Brick
Roughness		MediumRough	Smooth	Smooth	MediumSmooth	MediumSmooth	MediumRough	MediumF
Thickness	m	0.2033016	0.01	0.008467	0.01	0.019	0.0508	0.1016
Conductivity	W/m-K	1.729577	2	1.5996	0.38	0.16	0.03	0.69
Density	kg/m3	2242.585	2700	2700	1120	800	43	1920
Specific Heat	J/kg-K	836.8	753	423.6	840	1090	1210	790
Thermal Absorbance		0.9	0.9	0.9	0.9	0.9	0.9	0.9
Solar Absorbance		0.7	0.7	0.7	0.7	0.7	0.7	0.7
Visible Absorbance		0.7	0.7	0.7	0.7	0.7	0.7	0.7

Figure C.3: Materials object setup

specific heat, etc. are to be input which allows EnergyPlus to take into account the thermal mass of the material to evaluate transient conduction effects (Fig. C.3).

- Construction - The materials previously inputted are arranged in different

Class List

- [0002] MaterialProperty:GlazingSpectralData
- [0006] Construction
- [-----] Construction:CfactorUndergroundWall
- [-----] Construction:FfactorGroundFloor
- [-----] Construction:InternalSource
- [-----] WindowThermalModel:Params
- [-----] Construction:ComplexFenestrationState
- [-----] Construction:WindowDataFile

Thermal Zones and Surfaces

- [0001] GlobalGeometryRules
- [-----] GeometryTransform
- [0100] Zone
- [-----] ZoneList
- [-----] ZoneGroup
- [0698] BuildingSurface:Detailed
- [-----] Wall:Detailed

Comments from IDF

Explanation of Object and Current Field

Object Description: Start with outside layer and work your way to the inside
Up to 10 layers total, 8 for windows
Enter the material name for each layer

Field Description:
ID: A1
Enter a alphanumeric value

Field	Units	Obj1	Obj2	Obj3	Obj4
Name		GlzSys_8	Wall	Floor	Roof
Outside Layer		Glass_9803_Layer	Brick	Insulation Board	Lightwe
Layer 2		Gap_1_W_0_0165	Heavy Weight Conc	Heavy Weight Conc	Ceiling
Layer 3		Glass_9923_Layer	Insulation Board		Slate R
Layer 4			Wall air space resist		
Layer 5			Gypsum Board		

Figure C.4: Construction object setup

Class List

- Thermal Zones and Surfaces
 - [0001] GlobalGeometryRules
 - [0100] Zone
 - [0100] ZoneList
 - [0100] ZoneGroup
 - [0100] Surface:Detailed

Comments from IDF

Explanation of Object and Current Field

Object Description: Allows for detailed entry of building heat transfer surfaces. Does not include subsurfaces such as windows or doors.

Field Description:
ID: A1
Enter a alphanumeric value
This field is required.

Field	Units	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	Obj7	Obj8
Name		Surface 1	Surface 2	Surface 3	Surface 4	Surface 5	Surface 6	Surface 7	Surface 8
Surface Type		Floor	Wall	Wall	Wall	Wall	Wall	Roof	Floor
Construction Name		Floor	Wall	Wall	Wall	Wall	Wall	Roof	Floor
Zone Name		Thermal Zone 1	Thermal Zone 1	Thermal Zone 1	Thermal Zone 1	Thermal Zone 1	Thermal Zone 1	Thermal Zone 1	Thermal Zone 1
Outside Boundary Condition		Ground	Outdoors	Outdoors	Outdoors	Outdoors	Outdoors	Outdoors	Ground
Outside Boundary Condition Object									
Sun Exposure		NoSun	SunExposed	SunExposed	SunExposed	SunExposed	SunExposed	SunExposed	NoSun
Wind Exposure		NoWind	WindExposed	WindExposed	WindExposed	WindExposed	WindExposed	WindExposed	NoWind
View Factor to Ground									
Number of Vertices									
Vertex 1 X-coordinate	m	5	5	5	0	0	0	5	0
Vertex 1 Y-coordinate	m	0	0	-7	-7	-2	0	-7	6
Vertex 1 Z-coordinate	m	0	3.048	3.048	3.048	3.048	3.048	3.048	0
Vertex 2 X-coordinate	m	5	5	5	0	0	0	5	0
Vertex 2 Y-coordinate	m	-7	0	-7	-7	-2	0	0	0
Vertex 2 Z-coordinate	m	0	0	0	0	0	0	3.048	0
Vertex 3 X-coordinate	m	0	0	5	5	0	0	0	-3
Vertex 3 Y-coordinate	m	7	0	0	7	7	7	0	0

Figure C.5: Surface object setup

layers in this object starting from the outside layer to define the construction of the building (Fig. C.4).

- **Surface** - This object allows for detailed entry of building heat transfer surfaces. Each surface is defined in terms of its type, the thermal zone it belongs to, its construction, outside boundary condition and if it is exposed to sun and wind or not (Fig. C.5).
- **People** - This object models occupant effects on a space. For each zone, the calculation method for number of occupants is input, along with its activity schedule (Fig. C.6).
- **Sizing** - Specifies the data needed to perform a zone design air flow calculation. The calculation is done for every sizing period included in the input. The maximum cooling and heating load and cooling, heating, and ventilation air flows are then saved for system level and zone component design calculations (Fig. C.7).

Class List

Internal Gains

[0100] People

Comments from IDF

Explanation of Object and Current Field

Object Description: Sets internal gains and contaminant rates for occupants in the zone. If you use a ZoneList in the Zone or ZoneList name field then this definition applies to all the zones in the ZoneList.

Field Description: ID: A1 Enter a alphanumeric value

Field	Units	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	Obj7	Obj8
Name		Zone 1 People	Zone 2 People	Zone 3 People	Zone 4 People	Zone 5 People	Zone 6 People	Zone 7 People	Zone 8 People
Zone or ZoneList Name		Thermal Zone 1	Thermal Zone 2	Thermal Zone 3	Thermal Zone 4	Thermal Zone 5	Thermal Zone 6	Thermal Zone 7	Thermal Zone 8
Number of People Schedule Name		Zone 1 Occupancy	Zone 2 Occupancy	Zone 3 Occupancy	Zone 4 Occupancy	Zone 5 Occupancy	Zone 6 Occupancy	Zone 7 Occupancy	Zone 8 Occupancy
Number of People Calculation Method		People/Area	People/Area	People/Area	People/Area	People/Area	People/Area	People/Area	People/Area
Number of People									
People per Zone Floor Area	person/m2	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Zone Floor Area per Person	m2/person	0	0	0	0	0	0	0	0
Fraction Radiant		0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Sensible Heat Fraction		autocalculate	autocalculate	autocalculate	autocalculate	autocalculate	autocalculate	autocalculate	autocalculate
Activity Level Schedule Name		Zone Activity Sched	Zone Activity Sched	Zone Activity Sched	Zone Activity Sched	Zone Activity Sched	Zone Activity Sched	Zone Activity Sched	Zone Activity Sched
Carbon Dioxide Generation Rate	m3/s-W	0.0000000382	0.0000000382	0.0000000382	0.0000000382	0.0000000382	0.0000000382	0.0000000382	0.0000000382
Enable ASHRAE 55 Comfort Warnings		No	No	No	No	No	No	No	No
Mean Radiant Temperature Calculation Type		ZoneAveraged	ZoneAveraged	ZoneAveraged	ZoneAveraged	ZoneAveraged	ZoneAveraged	ZoneAveraged	ZoneAveraged
Surface Name/Angle Factor List Name									
Work Efficiency Schedule Name									
Clothing Insulation Calculation Method		ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc	ClothingInsulationSc
Clothing Insulation Calculation Method Schedule Name									

Figure C.6: People object setup

Class List

HVAC Design Objects

[0001] DesignSpecification:OutdoorAir

[0100] DesignSpecification:ZoneAirDistribution

[0001] SizingParameters

[0100] SizingZone

Comments from IDF

Explanation of Object and Current Field

Object Description: Specifies the data needed to perform a zone design air flow calculation. The calculation is done for every sizing period included in the input. The maximum cooling and heating load and cooling, heating, and ventilation air flows are then saved for system level and zone component design calculations.

Field Description: ID: A1

Field	Units	Obj1	Obj2	Obj3	Obj4	Obj5	Obj6	Obj7	Obj8
Zone or ZoneList Name		Thermal Zone 1	Thermal Zone 10	Thermal Zone 100	Thermal Zone 11	Thermal Zone 12	Thermal Zone 13	Thermal Zone 14	Thermal Zone 15
Zone Cooling Design Supply Air Temperature Input Method		SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu
Zone Cooling Design Supply Air Temperature	C	14	14	14	14	14	14	14	14
Zone Cooling Design Supply Air Temperature Difference	deltaC								
Zone Heating Design Supply Air Temperature Input Method		SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu	SupplyAirTemperatu
Zone Heating Design Supply Air Temperature	C	40	40	40	40	40	40	40	40
Zone Heating Design Supply Air Temperature Difference	deltaC								
Zone Cooling Design Supply Air Humidity Ratio	kgWater/kgDryA	0.0085	0.0085	0.0085	0.0085	0.0085	0.0085	0.0085	0.0085
Zone Heating Design Supply Air Humidity Ratio	kgWater/kgDryA	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Design Specification Outdoor Air Object Name		Outdoor Air	Outdoor Air	Outdoor Air	Outdoor Air	Outdoor Air	Outdoor Air	Outdoor Air	Outdoor Air
Zone Heating Sizing Factor									
Zone Cooling Sizing Factor									
Cooling Design Air Flow Method		DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay
Cooling Design Air Flow Rate	m3/s	0	0	0	0	0	0	0	0
Cooling Minimum Air Flow per Zone Floor Area	m3/s-m2	0.000762	0.000762	0.000762	0.000762	0.000762	0.000762	0.000762	0.000762
Cooling Minimum Air Flow	m3/s	0	0	0	0	0	0	0	0
Cooling Minimum Air Flow Fraction		0	0	0	0	0	0	0	0
Heating Design Air Flow Method		DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay	DesignDay

Figure C.7: Zone sizing object setup