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Holistic optimization framework for the operation of urban energy systems

Chiam Zhonglin

School of Computer Science & Engineering

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

2021

Statement of Originality

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Assoc. Prof. Arvind EASWARAN

Authorship Attribution Statement

This thesis contains material from three papers published in the following peer-reviewed journals / from papers accepted at conferences in which I am listed as an author.

Chapter 4 is to be submitted as Z. Chiam, I. Papas, A. Easwaran, C. Alonso and B. Estibals. Holistic optimization of the operation of a ground-source heat pump system: A case study on the ADREAM building in Toulouse, France. *Energy and Buildings*

The contributions of the co-authors are as follows:

- I. Papas assisted with the modeling, processing of data and manuscript drafts.
- Assoc. Prof. A. Easwaran provided the initial project direction, feedback on methodology and edited the manuscript drafts.
- Assoc. Prof. C. Alonso facilitated the initialization of the project.
- Assoc. Prof. B. Estibals assisted with the interpretation of the raw data.
- I chose the models, decided on the optimization strategy, generated the results and wrote the manuscript.

Chapter 5 is published as Z. Chiam, A. Easwaran, D. Mouquet, S. Fazlollahi and J. M. Villás. A hierarchical framework for holistic optimization of the operations of district cooling systems. *Applied Energy*, 239, 23-40 (2019).

The contributions of the co-authors are as follows:

- Assoc. Prof. A. Easwaran provided the initial project direction, feedback on methodology and edited the manuscript drafts.
- Dr. D. Mouquet provided input on the models and interpretation of the results.
- Dr. S. Fazlollahi provided feedback on the use of optimization methodologies.
- J. M. Villás assisted with the interpretation of the raw data.
- I chose the models, decided on the optimization strategy, generated the results and wrote the manuscript.

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The contributions of the co-authors are as follows:

- Assoc. Prof. A. Easwaran provided the initial project direction, feedback on methodology and edited the manuscript drafts.
- Dr. D. Mouquet provided input on the models and interpretation of the results.
- M. Gupta assisted with the implementation of the algorithms.
- I chose the models, decided on the optimization strategy, generated the results and wrote the manuscript.

18-02-2021

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Chiam Zhonglin

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“In the end, its all a question of balance.”

—Rohinton, Mistry

To my dear family

Abstract

The push for greater sustainability in urban energy use has led to increasingly complex systems - favoring greater extents of centralization and integration. Centralization of energy systems offers unrivaled levels of energy efficiencies and cost-effectiveness, a consequence of economies of scale. Shared infrastructures from centralized systems, further act as an enabler for facilitating the integration of alternative energy sources. These sources include renewable energy and the harvest of waste energy.

The incongruity between the design and operating conditions of these complex energy systems will always persist; it is inevitable to make assumptions given data limitations. When these conditions differ too vastly, the expected gains could easily be negated. Measures to improve the operation of urban energy systems could be explored through mathematical optimization on the appropriate models.

Components of urban energy systems are often operated at predefined setpoints or independently optimized - a repercussion of complexity. Localized control strategies inhibit the ability to adapt well under less-than-ideal scenarios, through the disregard of cascading effects on the system. Formulation of optimization problems that concurrently express these systems in its tuneable variables and captures the tight-coupling between the numerous components, i.e., holistically, usually results in a mixed integer non-linear program which is large and difficult to solve. To address this issue, abstraction techniques of judiciously selected models enabled the accompanying optimization problem to be formulated as a mixed-integer linear program. However, this technique has limited applications as it is highly reliant on case-study specific information.

For generic purposes, a hierarchical optimization framework for the operation of urban energy systems is introduced in the current work. In this framework, model abstraction techniques are first applied so that the resultant problem could be

solved using a combination of a genetic algorithm and a mixed-integer linear program solver. The metaheuristic is introduced to handle important decision variables that cannot be linearized. Using the mixed-integer linear program in tandem with the genetic algorithm effectively alleviates the computational effort, by reducing the search space of the latter. Since the reliance on the metaheuristic is reduced, the likelihood of achieving global optimality is increased.

The existence of energy storage systems, sanctions for energy to be stored in more favorable periods to be available later, thus enhancing cost-effectiveness and/or energy efficiency. Multi-period considerations demand optimization across several periods, burgeoning the size of the problem. Thus, the sliding-window technique is used in tandem with the hierarchical framework. This technique permits the trade-off between solution accuracy and problem size, hence resolution time and solvability. When the case-specific, size of the window (number of periods) is suitably chosen, the sacrifice in accuracy becomes justifiable, for the above-mentioned reasons.

Genetic algorithms are population-based metaheuristics and can require a considerable amount iterations to converge. This issue is further exacerbated in the framework where a mixed-integer linear program has to be solved in each iteration. For online applications, the genetic algorithm was substituted with a reinforcement learner. Implementation of the reinforcement learner allows part of the optimization load (learning) to be shifted offline, hugely speeding up the resolution time, when deployed online. Once trained, the framework only requires a single iteration to generate close-to-optimal solutions.

Finally, the three versions of the optimization framework were applied to case studies for illustration purposes. These case studies were based on an existing district cooling system and ground-coupled heat pump system serving a building. Results generated suggest substantial energy and cost savings of up to 31.9% and 12.7% respectively, when the operations were optimized for given energy demand.

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Symbols and Acronyms

Symbols

$\%$	fraction, percentage
Δ	difference
a	actor neural network
A	area (m^2)
c	critic neural network
C	monetary costs (€)
Cf	correction factor
Cp	specific heat capacity (kJ/kgK)
CO_2	carbon dioxide
COP	coefficient of performance
$\dot{E}$	electrical energy (kWh)
F	capacity constraint variable
Gi	global inclined irradiance arriving at a surface
k	TES loss coefficient
$Ktemp$	PV temperature coefficient
$loss$	system loss coefficient
$\dot{m}$	fluid flowrate (m^3/h)
$NTU - \epsilon$	effectiveness number of transfer units
$\mathcal{N}$	normal distribution
P	pressure (mH_2O)
$Pump$	hydraulic pump
pwl	piecewise linear segments
$\dot{Q}$	thermal energy (kWh)
R^2	coefficient of determination
st	stream variable

T	temperature (K , $^{\circ}C$)
t	time (h)
u, v	RLT variables
U	overall heat transfer coefficient (W/m^2K)
V	volume of thermal storage system (m^3)
W	linear weights
X	neural network
Y	binary on-off variable
$p, n, m, k, j, r, x, ..$	generic variables

greek letters

$\alpha, \beta, \gamma, \nu$	regression-derived constants
ϵ	effectiveness
η	efficiency
ω	angle ($^{\circ}$)
Θ	excess temperature, $T_{g,t} - T_{g_{init}}$ (K)
μ	mean
σ	standard deviation
δ	error
θ	neural network weights

superscripts

in	flow entering
out	flow exiting
n	generic number
min	lower bound
max	upper bound

subscripts

a	air
act	actor
amb	ambient

<i>app</i>	approach
<i>br</i>	branch
<i>c</i>	condenser
<i>cm</i>	cooling mode
<i>ch</i>	chiller
<i>cp</i>	common pipe
<i>cri</i>	critic
<i>ct</i>	cooling tower
<i>cold</i>	cold water
<i>d</i>	demand
<i>dist</i>	distribution
<i>e</i>	evaporator
<i>ele_rate</i>	electricity rate (€/kWh)
<i>exc_solar</i>	excess solar
$\dot{E}$	electrical energy (kWh)
<i>ESS</i>	electricity storage system
<i>g</i>	ground
<i>grid</i>	grid
<i>hm</i>	heating mode
<i>hp</i>	heat pump
<i>hot</i>	hot water
<i>init</i>	initial
<i>INV</i>	inverter
<i>limit</i>	limit
<i>loss</i>	losses
<i>mu</i>	make-up
<i>nwk</i>	network
<i>op</i>	operating
<i>OHM</i>	ohmic
<i>pump</i>	pump
<i>pv</i>	photovoltaic
<i>rq</i>	required
<i>s</i>	stored
<i>scm</i>	storage charging mode
<i>sdm</i>	storage discharging mode

<i>sel</i>	selected
<i>sf</i>	surface
<i>ss</i>	substation
<i>sys</i>	system
<i>t</i>	time-period
<i>u, v</i>	RLT variables
<i>unit</i>	collective, group, unit
<i>w</i>	water
<i>WAHX</i>	water-to-air heat exchanger
<i>wb</i>	thermodynamic wet-bulb
x_1, x_2, x_3	generic variables
<i>z</i>	zone
$0, 1, \dots, i, j, k, m, n$	generic labels
/	or
//	parallel

Acronyms

A2	actor-critic advantage
Adam	adaptive moment estimation
ADREAM	<i>architectures dynamiques reconfigurables pour systèmes embarqués autonomes mobiles</i>
ANN	artificial neural network
BIPV	building integrated photovoltaics
CP	condenser pump
COP	coefficient of performance
CCHP	combined cooling, heating and power
CNRS	<i>centre national de la recherche scientifique</i>
DCS	district cooling system
DPG	deterministic policy gradient
DDPG	deep deterministic policy gradient
DP	distribution pump
DHC	district heating and cooling
DHS	district heating system
DHW	domestic hot water

EP	evaporator pump
ELD	equal load distribution
ESS	electrical storage system
GA	genetic algorithm
GCHP	ground-coupled heat pump
GHE	ground heat exchanger
GNU	gordon-ng universal
GSO	group-search optimizer
HVAC	heating, ventilation and air conditioning
IEA	international energy agency
IoT	internet of things
LAAS	<i>laboratoire d'analyse et d'architecture des systèmes</i>
LMTD	log-mean-temperature-difference
MAE	mean-average-error
MDP	markov decision process
MILP	mixed-integer linear program
MINLP	mixed-integer non-linear program
MIQCP	mixed-integer quadratically-constrained program
MPC	model predictive control
Mtoe	million tonnes of oil equivalent
NLP	non-linear program
NN	neural network
OCL	optimal chiller loading
OF	objective function
PV	photovoltaic
QP	quadratic program
RL	reinforcement learning
RLT	reformulation-linearization-technique
RPM	revolutions per minute
SFEE	steady-flow-energy equation
SOC	state-of charge
TES	thermal energy storage
TRNSYS	transient system simulation tool
UEM	universal engineering model
WAHX	water-to-air heat exchanger

ZEB	zero energy buildings
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Chapter 1

Introduction

1.1 Context

Current energy use in the urban context has a consequential role in environmental degradation - motivating a spectrum of initiatives spanning from the development of alternative fuels, including renewables to techniques for efficiency improvements. As of 2018, the world's total consumption of energy stood at approximately 14 000 Mtoe, a rise of above 50% from a decade ago (*Figure 1.1*) [1]. Of which, above 85% of this consumption was derived from non-renewable sources such as coal, oil, and gas. This has contributed to unprecedented levels of CO_2 emissions which threaten to accelerate climate change at an alarming rate [2].

Buildings are responsible for up to 36% of global final energy use and 40% of CO_2 emissions with space conditioning and electricity usage as chief contributors [3]. Estimates from the international energy agency (IEA) highlighted the potential for buildings to be up to 40% more efficient than the current state. Improvements to these statistics must be made for urbanization to continue sustainably.

In 2019, renewable energies have not yet sufficiently matured to fully supplement global energy requirements, hence the necessity for integration with existing systems [4]. Centralization of urban energy systems offers unrivaled levels of energy efficiencies and cost-effectiveness - a direct consequence of economies of scale. Shared infrastructure from centralized systems, further function as a platform for facilitating the integration of alternative energy sources, which comprise renewables and

FIGURE 1.1: Reproduced graph of cumulative world energy consumption by fuel type [1].

waste energy harvest. Increasingly complex systems that emerge from the multiplex of energy sources and consumers, calls for equivalently capable management strategies to realize their potential for energy efficiencies.

The incongruity between the design and operating conditions of the complex urban energy systems will persist indefinitely; it is inevitable to make assumptions given data limitations [5]. When these conditions too vastly differ, the expected gains from centralization could easily be negated. Measures to improve the operations of these systems could be explored through mathematical optimization of the appropriate models.

Components of these systems are often operated at predefined setpoints or independently optimized - a repercussion of complexity [6, 7]. Inefficiency is further compounded by such control strategies; localized control inhibits the ability for systems to adapt appropriately under less ideal scenarios, by disregarding the cascading effect on the system. Formulation of optimization problems that both incorporate models with sufficient fidelity and captures the interdependencies amongst them usually results in a mixed-integer non-linear program (MINLP) which is large and difficult to solve. Hence, the primary focus of this thesis is to develop an optimization framework which is not only able to perform holistic optimization of the operations of complex energy systems but also has the potential to be utilized

in real-time. This framework is meant to function as a decision support tool for system operators.

1.2 Urban energy systems

Urban areas currently house more than 50% of the world's population, with this figure expected to approach 70% by 2050 [8, 9]. Improved economic and social opportunities in which cities offer serve as explanations for this observed trend [10, 11]. Consequently, as significant energy resources are channeled for the sustenance of the urban populations, cities account for much of the environmental pollution. In this thesis, 'energy systems' refers to an umbrella term for electricity, heating and cooling supply for buildings. The principal existence of such systems is to facilitate the conversion and transportation of energy for eventual consumption.

1.2.1 Centralization of energy systems

Centralization of energy systems has been the common theme for the past century where energy efficiency is concerned [12]. With varying degrees, centralization could occur at the building up to the district level. These systems offer many advantages over their decentralized counterparts in terms of economies of scale. By their sheer magnitude, they enjoy substantial economies of scale. The main benefits are summarized as follows:

- **Higher quality equipment.** The supply of energy becomes a utility that is delivered by a provider (state-owned or private company). Profit margins inevitably become paramount for competitiveness, necessitating the investment in energy-efficient equipment. Better resource utilization will result, hence, alleviating the burden on the environment. District cooling systems (DCS), an example of a centralized energy system, reported electricity savings of up to 20% over decentralized counterparts in Hong Kong [13]. The above-mentioned reasons also promote the reliability of energy supply.
- **Distribution infrastructure.** Whether in the form of cables or a network of pipes, they enable vastly greater flexibility in the selection of primary fuels

to generate the required energy supply. Decentralized counterparts typically only have singular choices. Centralized systems, thus have the flexibility to appropriate the right fuel type (renewables, etc.) for the purpose, without major infrastructural changes. This shared infrastructure also serves as a platform for the integration of alternative fuels in the future.

- **Demand aggregation.** Having a large system alleviates the need for smaller individual equipment from part-load operation - a commonplace scenario for decentralized systems. Operating efficiencies often peak at nominal loads, and greatly deteriorates otherwise. Opportunities for better design and control to further resource efficiency is also made possible with information derived from global monitoring systems
- **Consumer savings.** Maintenance of privately own equipment becomes redundant as energy becomes a utility to be purchased.

1.2.2 Integrated energy systems

The logical step which follows centralization is the integration of alternative energy sources to further the cause of energy efficiency. As it stands, energy generated from renewable sources is still intermittent, thus fossil fuels still hold an important role [14]. The integration of renewables not only has the benefit of relieving environmental burden but also an opportunity for engineers to build familiarity with operational know-how.

A classic example of an integrated energy system lies in that of a combined cooling, heating and power (CCHP) plant. Waste heat from power generation is used to fire up boilers and absorption chillers, for space conditioning purposes. Combining these processes, primary fuel efficiencies could be improved by two-fold - from a mediocre 40% to up to 80% [15, 16]. For urban systems, the complexity of integrated systems transcends that of mere process integration. Sporadic contribution from renewables and stochastic demand compounds the challenge of designing capable control strategies.

The permeation of the internet of things (IoT) into urban energy systems unveils a myriad of opportunities for improved design and operation [13]. Voluminous data generated by sensors deployed reveal trends that challenge conventional wisdom.

This is made possible by the rapidly increasing computational capacities and the abundance of functional algorithms. However, despite these technological advances, conservative design and operating procedures are still practiced, since urban energy systems are categorized as critical infrastructure, hence malfunctioning is a costly catastrophe which is never contemplated.

Nevertheless, research work exists to challenge the status quo. To accommodate the lack of experimental studies, virtual modeling is often resorted to, for testing and development of applicable solutions [17]. These methods, very often are targeted at efficient design and operation of an energy system such that electrical consumption is reduced. The primary objectives of design and operation studies are to select and schedule the various equipment (chillers, pumps, etc.), respectively, such that energy consumption and/or cost is reduced while meeting system constraints and satisfying end-user demands [18].

Independent operation of subdivisions of urban energy systems is a paradigm that should be shifted, given the current state of data availability and computing prowess. Although complex, there exists enormous potential to increase efficiency and reduce primary energy usage by integrating these processes. *Figure 1.2* summarized the five key aspects of urban energy systems [8]. The confluence of electricity and thermal energy from all sources, working in synergy and managed by advanced control systems for maximizing efficiency in meeting demand is archetypal of an ideal urban energy system. The result should be the following:

- Adaptable to changes in fuel, i.e., toggling between renewables and fossil fuels when required.
- Harvest of waste energy through process integration (e.g. waste heat harvest).
- Appropriate response to consumer demands, such that operational efficiency is maximized.
- Utilization of storage systems to reduce peak load.

FIGURE 1.2: Five elements of urban energy systems.

1.3 Motivation and problem statements

Despite the availability of data, estimates are inevitable during the design phase of urban energy systems. The deviation between design and operating conditions could be detrimental to varying degrees - depending on the type of equipment involved. A poorly designed system runs the risk of performing worse than even decentralized options. To further complicate matters, such infrastructures involve large capital investments and time to establish, thereby resistant to changes in design. Hence, methods to improve operation for a given system should be explored to ease the banes brought about by these discrepancies.

The vast majority of the work on the operation of urban energy systems fall into one of the two categories - simulation-based or optimization with highly abstract models. The benefits of conducting simulation lie in the ability to incorporate models of high fidelity, resulting in higher confidence for the results generated. However, highly detailed models are also more complex, making options for optimization very limited, explaining why simulation is often conducted instead. The converse is true the latter - while it is easy to perform optimization on highly abstract models, the results generated offer very little for operational improvement. To address this issue, this thesis focuses on the development of an optimization framework

that balances modeling fidelity with optimization compatibility for urban energy systems. The three fundamental issues addressed are as follows:

1. **Given an existing energy system, what is the best mode of operation to satisfy end-user demands while meeting system constraints?**

The existence of numerous decision variables, non-linearities, and tight-coupling amongst components, makes the determination of the optimal operating strategy a highly challenging task. For simplicity, existing work tend to focus on component-level optimization [19, 20] or utilize highly abstract models [21, 22]. While the solvability of the resulting optimization problem is indeed improved, with the design treated as a parameter, such techniques unnecessarily prune the already restricted solution space.

For the results of the optimization problem to be useful, two criteria must first be met. Firstly, the tuneable variables of the system need to be expressed as decision variables. The same demand could be satisfied with various combinations of decision variables, each with a different impact on system efficiency. This is especially true for thermal systems where a load can be fulfilled with many combinations of flowrate and temperature setpoints. Secondly, it is cardinal to capture the interdependencies amongst the system components and holistically optimize the system. Since a myriad of non-linearities exists in and amongst the models of system components, component-level optimization becomes overly naive.

The judicious choice of component models and the subsequent application of abstraction techniques enable the formulation of the resulting optimization problem as a mixed-integer linear program (MILP). However, this has limited applications and is hugely dependent on case-study specific information and objectives. For generalized applications, abstracted models are used with the introduced hierarchical optimization framework for optimizing the operations of urban energy systems. This approach decomposes the accompanying problem into its linear and non-linear segments and solves them sequentially, with the aid of the genetic algorithm (GA) and MILP. Doing so maintains the solvability of the problem and gives a higher certainty to globally optimal solutions while enables the model-related intricacies such as non-linearities, etc. to be factored. This framework is formally introduced in *Chapter 5* of this thesis.

2. How to balance between the resolution speed of the algorithm and the solution accuracy for multi-period optimization problems involving energy storage systems?

Energy storage systems complicate optimization problems as they require multi-period and multi-objective considerations. Although burgeoning problem sizes are a consequence, formulations across time-periods enable the solvers to sanction for energy to be stored in more favorable periods to be available later. Doing so can potentially enhance cost-effectiveness and/or energy efficiencies. Similarly, the extent of abstraction made in the related work while the offer relevant solutions to design-related issues are not suitable for the optimization of system operations [23, 24].

For solving such problems, the sliding-window technique is deployed in tandem with the hierarchical optimization framework [25]. Depending on the factors such as electricity pricing, energy demand, and size of the thermal storage, selection of the appropriate window size (number of periods), despite reducing the size of the concomitant optimization problem, still, deliver close-to-optimal results.

3. How to increase real-time applicability of the optimization framework?

Owing to the sheer number of conflicting decision variables and the non-convex nature of the problem, the holistic optimization of urban energy systems is a computationally intensive undertaking. This is the likely reason which inhibits the real-time deployment of algorithms for the optimization of operations. Where real-time control is concerned, model predictive control (MPC) techniques are often deployed for performance optimization [25]. While MPCs have the benefit of localized optimization through the use of simplified empirical models, significant cost and energy savings are disregarded without performing optimization at the system-level.

Reinforcement learning (RL) as a technique for optimal control is rapidly gaining traction for the closely related building systems [26]. However, system-level optimization is still shunned due to its complexity; only a small set of tuneable variables are chosen as decision variables [27]. Such techniques while they give insight into the applicability of RL algorithms, effectively disregard large segments of the solution space by ignoring the possibility of optimizing the remaining tuneable variables.

To address the issue of slow resolution speed associated with the hierarchical optimization framework, the GA is replaced with a RL. When coupled with the MILP in the hierarchical framework, the RL could be trained offline using data traces obtained from historical data. When the training is deemed sufficient and deployed in real-time, only one iteration of MILP is needed for generating the close-to-optimal solution. Although solution quality tends to be inferior to the GA, deployment of the RL enables the heavy computation (learning process) to be shifted offline, vastly speeding up real-time deployment.

1.4 Contributions and thesis organization

The main contributions of this thesis are summarized by chapter in the following.

1. **Chapter 2** presents the literature review done on related fields to the focus of this thesis - the evolution of urban energy systems, modeling of associated system components, associated simulation and optimization techniques. Finally, the gaps in the literature which motivate the current work are discussed.
2. **Chapter 3** documents component models which are required for the case studies in the ensuing chapters. The choice of models and complexity of the models are discussed.
3. **Chapter 4** highlights the benefits of abstracting the chosen models, as they permit the optimization problem to be formulated as a MILP. Several approaches to abstract the required models are discussed and subsequently applied to a case study based on an existing building-level ground-coupled heat pump (GCHP) system, which is integrated with solar photovoltaics and energy storage system. Multi-period and multi-objective considerations are essential to effectively model the electricity storage system and residual thermal energy from the ground. The abstraction of models enabled the system to be modeled with reasonable fidelity whilst maintaining compatibility with MILP solvers. Additionally, interdependencies amongst components could also be captured, giving useful insights into the bottlenecks of the system.

These insights prompted the addition of a theoretical water-to-air heat exchanger (WAHX) to function as an alternative to the ground for thermal exchange. Cost and electricity savings of up to 12.7% and 35% was achievable, suggesting that the additional investment cost is recoverable within five years.

4. **Chapter 5** introduces the hierarchical optimization framework, which is to be used with abstracted component models, for the optimization of the operations of urban energy systems. This framework is introduced to handle decision variables that could not be managed by the abstraction techniques alone. The key feature of this framework lies in the ability to holistically optimize MINLP problems by decomposing them into their linear and non-linear counterparts and sequentially solving them with the use of a GA and MILP solver. Indiscriminate use of metaheuristics on complex models is a common practice as evidenced by related work. Using a case study on an existing district cooling system (DCS) as an example, the benefits of the decomposed approach is highlighted by comparison against the sole use of the GA. For the predefined periods, the former always converged to a superior solution. Finally, the benefits of holistic optimization are highlighted through the counter-intuitive results generated by the framework for the given demand profiles. The energy efficiencies of a few major components in the DCS were compromised for the benefit of the entire system. Results from the case study indicated that an additional 18.9% of electricity could be saved when the DCS was optimized holistically as opposed to at the component level. This re-emphasizes the importance of modeling the non-linearities which are inherent to components and interdependencies amongst them, before performing optimization.
5. **Chapter 6** discusses the adaptation of the proposed optimization framework for compatibility with energy storage systems. Multi-period and multi-objective optimizations are required because of storage systems. Existing work, while they emphasize the importance of storage systems from the design perspective, offers little insight into the operation of system components, due to the use of models that are too abstract. The sliding-window technique was subsequently added to the proposed optimization framework for this undertaking. This technique performs optimization over a predefined number of periods (window size), but only uses the result for the first period. This is

successively done until all the required periods in the optimization problem is resolved. Doing so is beneficial greatly reduces the size of the accompanying optimization problem, hence the resolution time. While the result is an approximation of the global optimal, the difference is justifiable when compared to the improvement in solvability and resolution time. This technique was implemented in a case study based on a DCS. Results affirm the applicability of the technique and indicate that the window size is dependent on several factors, such as fluctuations in electricity price and capacity of the thermal storage system, for instance.

6. **Chapter 7** proposes the replacement of the GA in the optimization framework with a RL. This effectively increased the feasibility of the optimization framework to be deployed in real-time. Through the use of the RL, the heavy computation which is required to determine the relationship between the non-linear variables and the optimal solution could be determined (learned) offline, vastly speeding up the resolution time of the algorithm in real-time. As opposed to the original implementation involving the GA, the RL-MILP framework, when trained, just required a single iteration to deliver optimal solutions. Recently, RL is often suggested as a potential solution to some of the control-related optimization problems in energy systems. However, a highly limited number of variables are considered in the studies conducted. The training process for the neural network (NN) in the RL is an arduous task, especially when the output layer is larger than the input layer.

The combination of the RL with the MILP mitigates these issues, by having the MILP solve the bulk of the optimization problem. In doing so, the RL has to only determine the relationship between a handful of decision variables and the optimal solution. This not only reduces the size of the NN required and the training time but increases the likelihood of the solution quality. The capabilities of the RL-MILP approach is demonstrated using the same case study based on the DCS. Results generated, when compared against the GA-MILP approach showed only a 7.52% compromise in the optimal solution for a vast improvement in real-time algorithm speed.

7. **Chapter 8** provides a summary of this thesis and discusses some directions for furthering this work.

Chapter 2

Literature review

2.1 Overview

This chapter presents the latest work relevant to the optimization of urban energy systems. ‘Urban energy systems’ is generally used as an umbrella term for electricity, heating and cooling supply for buildings [28]. Both district and building-level studies on the two sub-topics are considered in this review as they are closely related. The literature review is structured into three main sections as listed below.

1. Evolution of urban energy systems
2. Optimization of urban energy systems
3. Review summary

2.2 Evolution of urban energy systems

The purpose of this section is to present a brief history of urban energy systems, discuss its current state and future trends. This information is an important consideration for positioning the current work and deciding on its future relevance.

2.2.1 History of urban energy systems

Centralized thermal energy systems began way before the advent of electricity - the first district heating system (DHS) was established in 14th century, in Chaudes-Aigues, France [29]. The heating system was established to collectively draw geothermal heat for the small village. Electricity generation followed suit in the 1870s when the Edison Electric Company established the first integrated power and lighting system in the streets of London and New York [30]. Towards the end of the same decade, DCSs emerged [31]. Common to all three systems, which the modern urban energy system is typically comprised of, centralization was undertaken to take advantage of economies of scale. The economy of scale which was traditionally derived from the transportation of energy supply has since evolved to also encompass operating efficiencies and control of complex equipment [32]. These systems are generally deployed for the sectors (industrial, commercial, etc.) with stable and highly predictable demand. Over the years (1870 - 2019), urban energy systems have also seen greater inclusion of sustainable energy sources, improvements in system design (storages, management systems, control algorithms, equipment, etc.) and a wider variety of sectors as well. In the current era of accelerated urbanization, urban energy systems are expected to be increasingly relevant, as inferred from the attention which they receive in the contemporary research [12].

2.2.2 Current state of urban energy systems

Electrical and thermal energy systems appear to be moving in opposite directions in terms of centralization, albeit at differing rates. For electrical systems, solar photovoltaics are increasingly being touted as a viable supplement to the power grid - a move away from centralization. The current share of building integrated photovoltaic (BIPV) systems account for 2.5% of the photovoltaic (PV) market and is expected to rise to 13% by 2022 [33, 34]. For thermal systems, however, district-level systems are gaining in popularity, especially in newer urban establishments [12, 35]. In general, these systems progressing away from fossil fuels and towards taking greater advantage of the environment sustainably and utilize energy more efficiently (waste energy harvest). Storage systems are also often utilized for the improvement of operating efficiencies.

2.2.2.1 Integration with sustainable sources

Integration with water bodies (sea, ocean, lake, etc.) to district thermal systems is an attractive option, as they offer thermal exchange with the environment at more favorable temperatures as compared to ambient air. This is especially true where cooling systems are concerned. Depending on the temperature of the water body in the region, chillers could even be done away with, resulting in very significant energy savings [36].

For regions with seasonal demands for cooling and heating, heat pumps are often used to harvest the thermal energy from the sea. The sea alternates its role as a heat sink and source during the summer and winter respectively [37, 38].

Integration with geothermal sources in this context refers to the naturally occurring heat sources and aquifers. Aquifers are underground layers of water-bearing permeable rocks that contain groundwater [39]. Due to the low thermal conductivity of soil and rocks, the temperature of the water remains invariant to ambient conditions; therefore it is relatively cooler in the summer and vice-versa in the winter as compared to ambient air [40]. When coupled with heat pumps, thermal energy could be harvested for both cooling and heating purposes. Aquifers are commonly used in one of the two ways - direct use of water for cooling or heating purposes or as a thermal storage facility. The benefits of using aquifers are discussed in [41, 42].

Borehole heat exchangers are usually deployed for thermal exchange with the ground [43]. Similarly in the absence of water, with the right type of composition and depth, the thermal inertia in the ground could be used for similar purposes. These systems are known as ground-coupled heat pumps.

Solar energy could power thermal collectors, absorption chillers and photovoltaics to fulfill heating, cooling and electricity demands respectively. These systems, tend to be lower in efficiencies than their traditional counterparts, however, not having to draw current from the grid meant lower emissions and operating costs. That, however, is only possible with a higher initial capital outlay for the appropriate equipment (PV panels, absorption chillers, etc.) [44, 45].

2.2.2.2 Process integration

Intergation of heat, power, and cooling into combined heating, cooling, and power plants could potentially offer unparallel efficiencies for the production of all three utilities. In these facilities, residual heat from the generation of electricity is used to fire up boiler and absorption chillers for heating and cooling respectively. Doing so can easily double the primary fuel efficiency [46]. The design of these CCHP systems are naturally more complicated than traditional power plants, much research on the improving the combination of variables such as steam pressures and temperatures to maximize the overall plant performance [21, 47–57].

Waste heat recovery from various processes (municipal solid water [58], electricity production [59–61], etc.) are commonly extracted and fire up heat pumps and chillers in district energy systems. Pinch analyses were often used to determine possibilities for such integration. The literature reviewed reported a reduction in fuel usage and CO_2 emissions of up to 41% and 60% respectively. Percentage savings, however, were highly influenced by the electricity price [62]. Especially where heating systems are concerned, the embracing of infrastructure for low-temperature networks, presents a highly viable option of integrating waste heat[63].

Integration with waste cold recovery is also a possible option, should there be a cooling system located in the vicinity of such processes. Natural gas and nitrogen, typically are imported in large cylinders and regasified into the network, releasing substantial amounts of cold energy [64, 65].

2.2.2.3 Role of storage systems

Energy storage systems permit the shifting of electrical and thermal load from peak to non-peak periods [66–68]. Both consumers and producers stand to benefit in terms of the improved energy performance of the energy systems which in turn translates into cost savings. Where thermal storages are concerned, water and ice are the preferred options. While water is the cheaper option, in certain scenarios, space-efficiency issues result in the preference for ice. Phase change materials have since been explored for the use with large scale thermal systems, however, they have yet to be feasible due to the lost of cost-effectiveness [69, 70]. For electrical systems, options for storage range from pumped hydro systems to lithium batteries

depending on scale [71]. Due to the advancement in battery technologies, the efficiency and cost of production of lithium batteries have dropped, hence it is becoming an increasingly popular option of building-level PV systems.

2.2.2.4 Losses in large-scale energy systems

Losses in electricity transmission are much lower than that of thermal pipelines [72, 73]. While there is currently not an easily available alternative for grid electricity in urban areas, there exist many decentralized options with the low capital cost for thermal systems, making urban thermal systems more price elastic. Therefore, there is a greater imperative to minimize distribution losses in the thermal network.

The majority of the losses occurring in district heating and cooling systems occur in the distribution network. The two main sources of thermal losses (temperature degradation) are to the environment and pumps. These losses are much more pronounced than in decentralized systems, due to the need to pump water over large distances to reach the consumers who are connected to the network. These large distances also incur considerable head losses, requiring the pumps to work even harder.

Surfactants could be introduced to reduce the viscous losses at the fluid-pipe interface. Drag coefficients reduction of up to 80% has been reported in the state-of-the-art, significantly reducing the power required for pumping [74]. Considerable research was invested in the attempt to reduce thermal losses to the environment by working with fluid temperature which is closer to ground temperatures. That resulted in the widely popular low-temperature district heating networks [63, 75]. In cooling networks, however, the temperature difference is small, leaving little room for adjustments, hence guidelines for design such as the maximum radius of the network, etc., are adhered to [12].

2.2.2.5 Future trends

In the absence of revolutionary technologies that could radically improve energy efficiencies and cost-effectiveness where the production of heating, cooling, and electricity are concerned, researchers have unanimously agreed that higher levels of integration with sustainable sources should be pursued [76]. This, however,

implies that the design and control measures that govern these systems must correspondingly evolve [12, 77].

The residential sector represents a large untapped potential for urban energy systems due to the unpredictability of demands. Electricity, for instance, is usually priced similarly throughout the day, unlike their commercial and industrial counterparts. As the demand increases, due to the impending introduction of newer technologies (electric cars, etc.), control measures need to improve in tandem to reduce inefficient operation due to unnecessarily high peak loads. The control of thermal systems should also mirror that of the electrical grids, enabling bi-directional purchase and sale of energy whenever appropriate [78].

2.3 Optimization of urban energy systems

This section reviews the existing optimization work related to urban energy systems. The objective of this review is to identify how such problems are approached in the state-of-the-art, i.e., determination of objectives, variables, simplifications and choosing algorithms to solve them. The literature on both district and building level problems are included in this review.

2.3.1 Design optimization

Optimization pertaining to the design of urban energy systems attempt to determine the best configuration of equipment type, primary resource, distribution route and variability of consumer profiles, which would result in the highest possible efficiency. Such formulations typically employ highly abstract models, which tend to regard many otherwise tuneable variables as constants. Owing to the complexity performing optimization holistically, i.e., at the system-level, an overwhelming majority of the case studies reviewed performed optimization on components locally (heat pumps, network, etc.). The popular objective functions are investment cost, electricity consumption and to a much lower extent, CO_2 emissions.

2.3.1.1 Mono-objective

Building-mix. The ‘optimal’ combination of consumers (type, demand profile, etc.) heavily impacts the resulting efficiency of the energy system. Components belonging to these systems typically have small operating ranges where efficiency values are at their highest. Large fluctuations in demand are extremely detrimental as they are solely responsible for dips in efficiency which propagates through the system, causing poor performance of ancillary components too. Metaheuristics have been used during the design phase to minimize the stochasticity of the cumulative demand profile through the lens of the centralized system by selecting the best mix of consumers [79].

Network design optimization attempts to determine the best placement of nodes (central station, substations, transformers, etc.) and edges (transmission lines) for the minimization of a certain objective function. For thermal systems, some case studies even consider the sizing of pipelines.

For highly simplified problems, the network design could be modeled as a set of nodes and edges, with fixed/linear weights attached to each edge. Such formulations could be solved using Dijkstra’s algorithm [80], linear weights, on the other hand, are formulated into MILPs [81, 82]. These problems were formulated with estimated demand profiles as hard constraints that cannot be violated. However, the treatment of non-linearities (temperature, pressure, etc.) as constants may adversely impact the feasibility of suggested solutions.

Where the non-linear variables are considered, metaheuristics are commonly deployed. For greater accuracy, analytical equations were used to estimate the required pumping power and hence the investment cost of pumps [80, 83, 84]. Metaheuristics are hugely popular because of their ease of implementation and relatively decent performance in the search for an ‘improved’ solution.

System-level design pertains to the sizing of equipment in the central plant and the transmission/distribution network to most efficiently fulfill the demands of consumers. Often, the sizing of the major system components receives the greatest attention as they are perceived to have the largest impact on the system. Furthermore, due to the complexity, models used are usually highly minimalistic. Black-box modes with constant efficiencies regardless of load factor is one such

example, used in many CCHP optimization studies [21]. Through simplification, the inclusion of a wider array of components (alternative sources, solar, etc.) was still possible whilst still maintaining the problem's MILP feasibility. Simplifications, inevitably neglect some tuneable variables which may have the objective function may be sensitive to, should conditions deviate from the presumed state [48]. The technique known as the 'reformulation-linearization-technique' (RLT) could be used to linearize bilinear variables in optimization problems [85]. This enabled more variables to be optimized by MILP solvers.

Uncertainties such as the impact of improper maintenance, malfunction, reduced performance, weather, design, construction, and outdoor conditions could be considered with the aid of techniques such as the Markov method [86] and minimax regret theory [87, 88] in optimization problems. Through sensitivity analyses, it was deemed that the objective function was most sensitive to the design of buildings, above the other considered factors.

2.3.1.2 Multi-objective

Evolutionary algorithms are often used to generate solution sets for multi-objective optimization problems concerning urban energy systems. Total investment cost and CO_2 emissions are the most commonly chosen objectives. The Pareto frontiers of these two objectives are usually discontinuous with many points of local optimums [89, 90].

To incorporate more decision variables into the problem formulation, a decomposed optimization approach was used by Fazlollahi et al. for the optimization of district heating systems [91–93]. In this approach, the non-linear and linear aspects of the optimization problem are first separated and solved sequentially with the use of evolutionary algorithms and MILP solvers. To further improve the resolution speed of the approach, load clustering algorithms were used to reduce the size of the input data.

2.3.2 Operation optimization

Estimations are inevitable during the design phase of urban energy systems due to the lack of information. Consequently, the performance of the resultant energy

system, when operational tends to be lower than expected. Optimization of control measures could be used to reduce this deficit.

Given the design of an urban energy system as an input parameter, the purpose of such optimization problems is to determine modes of operation so that the energy demands are met in the most efficient manner. Thus, the task involves finding the combination of component-level variables such as flowrate, temperature, pressures, loading-factors, etc., to fulfill the given objective. This calls for component-level models that reflect a much higher level of fidelity than design level problems. Such models involve highly complex governing equations which naturally conflicts with the innate requirement borne by operational optimization algorithms - to deliver solutions within a reasonable amount of time. Complexity is further compounded at the system-level, making the resultant optimization problem to solve a huge challenge. To balance between the aforementioned preconditions, researchers typically resort to highly simplified models of the system, tuning only a small subset of variables. The result is often a collection of locally-optimized sub-systems, which disregard substantial energy-saving potential.

2.3.2.1 Mono-objective

District level optimization studies typically involve highly integrated energy systems which not only involve multiple energy sources and types but also encompass both production and consumption. The minimization of operating costs and, to a lesser extent, energy consumption, are the most commonly defined objective functions. A classic example of a district-level multi-energy system is one which includes energy production from fossil fuels, wind and solar, generating electricity and heat using turbines, boilers, heat pumps, and fulfilling demands through an extensive distribution network of cables and pipelines [94]. To derive meaningful insights concerning the operation of these systems, detailed models, involving non-linear differential equations are commonplace to represent each component. These models enable tuning of a wider range of variables, oftentimes, even defining the usefulness of the solution derived. For instance, a heat pump can produce the same quantity of heat with a range of flowrate and temperature combinations, each impacting energy consumption differently. To cope with the behemoth task of solving the optimization model, the application of metaheuristics are hugely popular in this domain [95, 96]. While the resolution speed of the optimization is inconsequential

for feasibility studies, the truth is not symmetrical for those with practical aspirations. Various techniques have been deployed to simplify optimization models. Sakawa et al.'s model of the district heating and cooling system strictly restricts the GA's optimization variables to binary values, improving resolution speed three-fold, while maintaining solution quality when compared to traditional branch-and-bound methods [97, 98]. The simplification meant, however, that the optimizer could only decide which of the components to operate, not their operating point. Operators of energy systems, although contractually obligated to fulfill the energy demands of consumers can sometimes choose to violate the agreement and pay a penalty instead; such considerations enable the relaxation of binding constraints, widening the solution space, and gaining insights into counter-intuitive measures [99].

With the appropriate choice of parameters and equation-based models of heat-pumps, the initially complex MINLP model of the district heating and cooling system could be broken down into smaller quadratic programs (QP) and solved sequentially [19]. The formulation of the QP hinged on the inherent properties of the complex governing equations of the heat-pump model which only holds if the temperature-related variables were held constant. In addition, load aggregation and the removal of binary variables were necessary to ensure the applicability of this method. The primary benefit of the QP formulation resides in the improvement of solution quality and exploiting the resolution speed of well-established QP solvers.

Building-level optimization problems tend to place greater emphasis on the major components of energy systems. For instance, the 'optimal chiller loading' problem is often the primary focus where cooling systems are concerned. Building systems, unlike district-level systems, have significantly lower energy expenditure on distribution, hence justifying the lack of focus on ancillary components. Metaheuristics are often used on these highly detailed models to solve the economic dispatch problem. In such studies, algorithms such as the GA and swarm-based algorithms are applied directly to optimize the differential equations describing the components (e.g. chillers) [100, 101]. Hyperparameters tuning and the implementation of these algorithms are the primary focus of these studies. In some cases, the differential-equation based models are reduced into polynomial equations, within a defined boundary using regression [102]. The electricity consumed by a chiller could be expressed as a quadratic or cubic function of the total cooling load, should the

operating temperatures be parameterized. Doing so enables the deployment of well-established convex optimization techniques such as gradient-descent to solve for the optimum. These studies prove that additional energy savings are possible with models of higher fidelity, i.e., the cubic model. Comparisons between convex optimization techniques and metaheuristics yielded little differences in the quality of final solutions, with the former edging slightly ahead when it comes to consistency when trials are repeated, due to the absence of the element of randomness within the algorithm [103].

Optimization in real-time typically refers to a requirement where operating strategies must be determined just-in-time for deployment. In these cases, the selected algorithm will be tasked to optimize the system using predictions of energy demands for subsequent time-periods. These periods range from minutes up to two hours, making the resolution speed of the optimization methodology of critical importance. These are known as MPCs. MPCs have since evolved from classical controls such as gain scheduling to the incorporation of mathematical programming and even machine learning techniques. However, despite the sophistication of techniques involved, cognizant of the importance of the resolution time, optimization models developed are still largely small and localized to components of the system [104, 105].

To optimize the control of a chiller system, Cox et al. developed a methodology involving the use of artificial neural networks (ANN) and GA for optimizing the hourly energy consumption[106]. In this study, the ANNs were trained using outputs from physics-based models of components for a select subset of optimization variables with the primary purpose of hastening resolution speed under time-sensitive applications. Subsequently, the GA is used to optimize the inputs to the ANN-based model for a given cooling demand, yielding superior levels of energy efficiencies compared to traditional rule-based control strategies. In cases where models are data-driven and extrapolation outside the operating range is required, polynomial approximations of component models are preferred to that of using ANNs. Besides the extrapolation capabilities, properties of polynomial equations further enable the formulation of the optimization problem into mathematical programs such as a MILP and the corresponding use of robust methods to solve them [25].

As a technique for optimal control, RL is rapidly gaining traction in the field of building energy control [107]. RL utilizes concepts from Markov decision processes (MDP), by allowing an agent to be rewarded by taking good actions in the environment under a given state. In the field of urban energy systems, the environment, action, state, and reward refer to the system, mode of operation, operating conditions (weather, demand, etc.), and objective function (cost, energy consumption, etc.) respectively. The complex relationship among the state, action, and reward is captured using NNs. RL has been applied to energy systems in many aspects, ranging from lighting control, domestic hot-water to building climate control applications. For building climate control studies, model-free approaches utilizing the deterministic policy gradient (DPG) and actor-critic advantage (A2C) algorithms are commonly applied directly on simulation tools such as EnergyPlus, for the optimization temperature-related variables. Training stability and convergence of the agent are major issues which the majority of studies reviewed, attempt to address. Li et al. deployed improved the training stability adding recurrent capabilities and pre-training the agent NN using offline data-traces [27]. In a similar study conducted by Brandi et al., it was found that the use of relative parameter values to describe the state space was the primary reason for improved training stability [108]. The stability of RL-based techniques appears to be the largest obstacle to implementation, evidenced by the number relatively low percentage of experimental verification studies conducted [107].

2.4 Review summary

Urban energy systems trends towards heightened levels of centralization and energy integration for increased efficiencies and reduced emissions. This makes control measures of such systems increasingly challenging, due to the sheer number of variables to tune, while considering interdependencies of these components. Given the inherent non-linearities in, and amongst component models, it is thus paramount to factor these considerations in the formulation optimization problems. The review of studies pertaining to the design of urban energy systems elucidates the benefits of extensive consideration of components, ranging from primary to ancillaries and their impact on the objective function. Studies on operations however are vastly focused on the simplicity of optimization models as they have a direct impact on the

resolution speed of the algorithm. Modeling such intricacies, although they result in better solutions through a wider solution space, are often not computationally feasible to solve.

The following are some gaps in the literature which pertain to the global optimization of the operations of these systems.

1. Component models used in studies pertaining to operation optimization problems are typically highly simplified, permitting the tuning of only a small subset of variables. As an example, where thermal systems are concerned, only quantities of energy flows are considered, without clear indications of the exact steps required for execution. Heat pumps could easily deliver the same quantity of thermal energy with an infinite combination of flowrates and temperatures, each bearing a significantly different impact on efficiencies. Greater optimization opportunities could exist in the removal of assumptions made for the sake of model simplification. The overall value-add to the system is likely to be significant, due to the cumulative effect of exploring the solution space mapped by these high-fidelity models thoroughly.
2. The modeling of ancillaries is often ignored in operation optimization studies; it appears that only models of the major components are considered for optimization. The benefits of considering ancillaries such as pumps and the transmission networks are highlighted in the review of design-related optimization studies on urban energy systems. While it may be acceptable to neglect the impact of the transmission network in building-level thermal systems, the same cannot be said at the district-level. For the latter, appreciable quantities of energy are expended for delivering the utilities over considerable distances. In addition, losses in that process are also more likely to be more pronounced, again evidenced by studies on design-related problems. Inclusion of the transmission network is therefore highly likely to play a profound role in the determination of the optimal operation of larger energy systems.
3. Component-level optimization is ubiquitous in operation-related studies, i.e., optimized independently from each other. This is likely due to balancing modeling complexity and the resolution speed of the optimization algorithm. While it is generally true that such practices may give results that are superior to traditional rule-based operating techniques, the interaction amongst

components and their ancillaries, should not be ignored as they are likely to be much more pronounced in these large and increasingly complex integrated, district-level systems. It is thus, not too inconceivable to operate some major components inefficiently for improved system-level performance, for the relationship amongst components evolves to become less apparent.

4. Energy storage, especially in thermal systems, is hardly a feature where operation optimization studies are concerned. This is probably due to the burgeoning size of optimization problems, affecting computational efficiencies since consideration across several time-periods have to be incorporated. Feasibility studies have proven that energy storages are well-positioned to leverage lower energy costs during off-peak periods, under relatively restrictive control policies - charge during the night, discharge during the day. Should these control policies be less restrictive, these systems could be further utilized to influence the operation of other components of the energy system. For instance, should the operation of thermal storages be optimized at the hourly-level, scenarios such as charging during periods of high energy cost could occur as it improves the efficiency of the overall system by operating at a higher loading factor. To yield more optimized operating solutions by improving the time-granularity at which energy storage is operated, methods to improve modeling and solving such problems are required.
5. The literature on the real-time optimization of urban energy systems is excessively focused on three aspects - hyperparameter tuning, reward-shaping, and training methods. The improvement in the quality of system models where RLs can be deployed as an optimization technique seems to be lacking. Fundamentally, the agent NN will probably converge more readily when the action space is reduced. Reduction in the action space can be achieved via prudently chosen optimization models. Hybridization with well-established optimization solvers could be one avenue worthy of exploration.

This thesis is positioned to address the above-mentioned gaps in the literature. Firstly, abstraction techniques were applied to carefully chosen models which reflect the suitable level of detail to the problem formulation. These techniques balanced modeling fidelity with optimization compatibility. Where model abstraction alone is insufficient, a hierarchical framework was introduced to be used in tandem with

these abstracted models. This combination provides a systematic approach for optimizing complex energy systems, holistically. Finally, to handle the demands of energy storage systems and real-time optimization, the sliding-window technique and RL were also incorporated in the developed framework.

Chapter 3

Model selection and abstraction

3.1 Overview

The selection of component-level models of energy systems used for case studies in this thesis is presented. Firstly, a brief survey of compatible component models is conducted before justifying the final choice. The selected model is then abstracted as much as possible so that it is compatible for formulation as a MILP. These two aspects are discussed in greater detail in the ensuing subsections. The purpose of this chapter is to provide a background of the abstracted models which will be repeatedly used throughout this thesis.

Two case studies based on existing urban energy systems are used for illustration in this thesis - the first is based on a building-level GCHP system and the second, a district-level cooling system. *Table 3.1* summarizes the list of component-level models required for each of the case studies. Complete formulations require the proposed optimization frameworks, which will be discussed in detail, in the later chapters (*Chapters 4 to 7*).

3.2 Component-level models from the literature

Component-level models, from existing literature, which are required by the case studies in this thesis are reviewed in this subsection (*Table 3.1*). The understanding of these models is crucial to the formulation of optimization problems and the

		<i>Chapter 4 :</i> GCHP system	<i>Chapter 5 and 7 :</i> DCS	<i>Chapter 6 :</i> DCS + thermal storage
Component	Heat pump/chiller	✓	✓	✓
	Cooling tower	✓		✓
	Pump + network	✓	✓	✓
	Heat exchanger	✓	✓	✓
	BIPV	✓		
	Ground heat exchanger (GHE)	✓		
	Electricity storage system (ESS)	✓		
	WAHX	✓		
	Thermal energy storage (TES)			✓

TABLE 3.1: Component-level models required in each case study.

development of the corresponding strategies for solving them. Models that are considered here extend beyond those already used the related work on similar problems, as they are usually too simplified. The purpose is to first identify before abstracting them into black-box models that are compatible with optimization algorithms. The complexity of these models has a direct impact on the range of compatible optimization techniques.

3.2.0.1 Heat pumps / chillers

Chillers are just heat pumps operated in reverse, thus they could be represented by the same model. They represent one of the more efficient methods of cold and hot energy production in urban energy systems. Black-box models of heat pumps must accurately predict the coefficient of performance (COP , a metric of efficiency) over a range of operating conditions (load, temperatures, etc.). The heat pump models are categorized into four groups - iterative, regression, thermodynamic and machine-learning-based models.

The ‘elemental $NTU - \epsilon$ and the simultaneous equation models are two iterative models of heat pumps [109, 110]. Both models attempt to simultaneously solve for the governing equations for each subcomponent of the heat component (compressor, evaporating-valve, evaporator, and condenser).

Several regression-based models have also since been developed [111–116]. The complexities of the models range from linear to multi-variate polynomial. Although these models have no physical significance, they perform well in the working range which they were used for.

Thermodynamic models are based on the linear relationship between the reciprocal of COP and thermal load and the irreversibilities of thermal transfer [117]. Based on this observation, three models were developed [115, 117–124]. Each of the three models was developed for differing purposes, evidenced by the difference in variables considered. Since they are based on analytical formulae, they exhibit the best extrapolative properties, performing well with very limited training datasets [111, 116].

Machine-learning techniques have also been used to model heat pumps, and they exhibited the best predictive capabilities, within the training dataset [125].

3.2.0.2 Cooling towers

Cooling towers are often used to dissipate heat from the condenser side of the heat pumps when used for cooling (chillers). This is primarily done by taking advantage of the cooling effect from evaporating water. The evaporation of water thus, involves differential heat and mass transfer equations, making these models mathematically involved. Thus, iterative methods are employed to solve such equations [126]. A simpler model proposed by Lu et al. used Taylor’s series expansion to make polynomial approximations of these differential equations [127]. That resulted in a regression-based model.

3.2.0.3 Pump and network

The pump and network need to be modeled simultaneously due to their high degree of dependence. The Darcy-Weisbach equation is often used to describe the pressure-flowrate relationship of fluid motion in pipes. Pump models used in related problems are often regression-based, relating power consumption directly to the flowrate [80, 83, 84]. This implicitly implies that the pressure requirements for any given flowrate are always satisfied.

3.2.0.4 Heat exchangers

All types of heat exchangers are either modeled using the effectiveness-NTU ($\epsilon - NTU$) or log-mean-temperature-difference (LMTD) method [128]. The $\epsilon - NTU$ method is easier to deploy when there is limited information about the operating temperatures of the heat exchanger. Correction factors may have to be added if the configurations deviate from the classical ones.

The modeling of GHEs requires additional considerations such as variation in the ground temperatures, which is typically ignored [129]. The fluctuation of ground temperatures has a significant impact on heat pump based systems. Not considering that will result in a gross over-estimating of operating efficiencies. A ground heat exchanger model, considering the dynamic variation in temperature was formulated for solving with a hybrid differential evolution algorithm [130]. This model takes into consideration the thermal resistance model of the ground, by incorporating soil properties. As evidenced by the results obtained, the variation in ground temperatures had a very pronounced role in the optimal operation plan. A closely related study validated this effect experimentally [131]. Through experimental results, an empirical ground temperature model was developed.

3.2.0.5 Building integrated photovoltaics

The accurate modeling of solar photovoltaics depends on the consideration of several variables - such as the surface area, angle of irradiance, working temperatures, etc. As such, tools from Matlab's Simulink toolboxes are often favored for modeling the individual components in which the solar panel is comprised of [132, 133]. The governing equations of each subcomponent are then solved using iterative methods. Where accurate black-box models are required, neural networks were employed [134]. In a bid to develop a simplified empirical model for estimating the usable electricity produced by a solar panel, Neuhaus et al., combined several empirical equations from previous work in literature. That resulted in a multivariate single equation photovoltaic model with prediction accuracies comparable to simulations from commercial programs [135].

3.2.0.6 Electricity storage systems

Accurate modeling of electricity storage systems (batteries), require variables such as current, voltage and the state-of-charge (SOC) to compute the percentage of usable electricity stored in the battery. Typically, equation-based models encompassing these variables are utilized [136]. Battery losses occur due as a result of internal resistance, which correspondingly increases as a function of the SOC. These losses are significant and can amount up to 50% when the battery is near its maximum charge capacity [137]. Most optimization studies deploy battery models with constant charge efficiencies and only consider the input and outputs of usable electricity, measured in kilowatt-hours (kWh) [138].

3.2.0.7 Thermal energy storage

TES systems can come in many forms, however, in this thesis, only water storage tanks are required for the case study. The inclusion of TES systems into optimization problems requires consideration over several time-periods, making the resulting formulation quite sizable. Often, assumptions such as fully-mixed, singular temperature layers are considered for simplification purposes [139]. To make models more realistic, upper and lower bounds of temperature ranges were considered in an MINLP formulation [140]. In an era where MINLP is still not tractable for reasonably sized problems, a MILP formulation for water storage tanks, considering thermal stratification was developed [141]. This model discretizes the thermal stratification in the tank. and expresses both the temperature and volume of water stored as decision variables. The bilinear relationship between these variables was linearized using Taylor's approximation. The reduction of the formulation into a MILP greatly increases the solvability of the problem.

3.3 Model abstraction

Models that are chosen to represent the components of energy systems in the two case studies are discussed in this section. The following two considerations heavily influence the eventual choice of models.

1. **Extrapolation capabilities** Data points obtained from the case-studies are largely confined to the operating policies the components are subjected to. This means that although permissible through manufacturer’s specifications, the range of possible operating conditions was never fully explored. Thus, it is not only necessary for the chosen models to be calibrated using measured data, but also contain a degree of analytical aspect. The analytical aspect will contribute to a greater degree of confidence when extrapolating the output of the model beyond the range it has been calibrated with.
2. **Compatibility with mathematical programming** Based on the literature reviewed in *Chapter 2*, it appears that the solving method hugely depends on the choice of models for representing the energy system. Metaheuristics and mathematical optimization methods are deployed when models are complex and simplified respectively - a middle ground does not seem to be present. Therefore, the purpose of this section is to present abstraction techniques for improving the compatibility of high-fidelity models for mathematical programs.

Equation-based models are preferred as they give a clear insight into the ‘class’ which the resultant optimization problem might fall into. Manipulation and/or simplification of these equations allow the deployment of well-known techniques (convex, MILP, etc.) and solvers that have a good estimate of the optimum. These models are formulated such that they contribute directly to the primary objective function, which is defined to be electricity consumption.

The abstraction of the selected models to suit a MILP formulation is discussed in the following subsections. MILP was chosen due to the availability of solvers and its widespread use in related problems [18]. In each of the following subsections, justification of the chosen model is first provided, followed by the abstraction and finally, discussion on the error incurred in the process. Through the application of these techniques, it is also paramount to ensure that the abstracted models preserve the unique characteristics of the parent model derived from. Discussions of the error incurred are only presented for models which have been linearized, with the example plots taken from case studies which will be presented in *Chapters 4* and *5*.

3.3.1 Electric heat pumps

3.3.1.1 Description

Electric heat pumps are a central component of the two case studies. They produce heating/cooling by extracting and rejecting heat at the evaporator and condenser respectively. *Figure 3.1* illustrates the schematic of a generic electric heat pump. The primary objective of this model is to express the *COP* in terms of the independent (tuneable) variables listed in *Table 3.2*. *COP* is essential in the determination of electricity consumption and exhibits a highly non-linear relationship with these variables; hence a model is required.

FIGURE 3.1: Schematic of a vapor compression electric heat pump.

Independent variables	Dependent variables	Constants
T_e^{out}	COP	Cp_w
T_e^{in}	$\dot{Q}_e$	
$\dot{m}_e$	$\dot{Q}_c$	
T_c^{in}	$\dot{E}_{hp}$	
T_c^{out}		
$\dot{m}_c$		

TABLE 3.2: Independent variables, dependent variables and constants related to the electric heat pump model.

3.3.1.2 Selected model

Gordon-Ng universal chiller model (GNU) is selected to represent the generic heat pump [123]. The model is based-off analytical equations and can be calibrated with raw data. It is a grey-box model that incorporated laws of thermodynamics and energy balances at heat exchangers with some assumptions of internal and external energy losses. As a result, it displays relatively good predictive capabilities (including extrapolation) despite limited data points [111, 116]. The describing equation for this heat pump model is as follows,

$$\frac{T_e^{in}}{T_c^{in}}(1 + \frac{1}{COP}) = \beta_0 \frac{T_e^{in}}{\dot{Q}_e} + \beta_1 \frac{T_c^{in} - T_e^{in}}{T_c^{in} \dot{Q}_e} + \beta_2 \frac{\dot{Q}_e}{T_c^{in}}(1 + \frac{1}{COP}) \quad (3.1)$$

where β_0 , β_1 and β_2 are derived using regression with raw data.

The steady flow energy equation (SFEE) is invoked [142] to relate $\dot{Q}_e$ and $\dot{Q}_c$ to their respective fluid flowrates.

$$\dot{Q}_e = \dot{m}_e \times C_{p_w} \times (T_e^{out} - T_e^{in}) \quad (3.2)$$

$$\dot{Q}_c = \dot{m}_c \times C_{p_w} \times (T_c^{in} - T_c^{out}) \quad (3.3)$$

The heat rejected at the condenser side is the approximate sum of the compressor work, and the cooling effect produced at the evaporator side for steady-state operation. A constant is added so that the following equation can be calibrated with raw data. Doing so accounts for the inefficiencies in the compressor (i.e. compressor work $\leq \dot{E}_{hp}$).

$$\dot{Q}_c = \alpha_0 \times (\dot{Q}_e + \dot{E}_{hp}) \quad (3.4)$$

where α_0 is derived using regression.

Finally, the relationship between COP , $\dot{Q}_e$ and $\dot{E}_{hp}$ is,

$$COP = \frac{\dot{Q}_e}{\dot{E}_{hp}} \quad (3.5)$$

3.3.1.3 Model abstraction

The characteristic electric heat pump equation described by the GNU model needs to undergo a certain level of abstraction so that it can be formulated as a MILP. The aim is to express the dependent variable $\dot{E}_{hp}$ in terms of its input variables as linearly as possible. The following steps illustrate how the model is simplified.

1. Use *Equation 3.5* to substitute COP terms in *Equation 3.1* with $\dot{E}_{hp}$.

$$\frac{T_e^{in}}{T_c^{in}}(1 + \frac{\dot{E}_{hp}}{\dot{Q}_e}) = \beta_0 \frac{T_e^{in}}{\dot{Q}_e} + \beta_1 \frac{T_c^{in} - T_e^{in}}{T_c^{in} \dot{Q}_e} + \beta_2 \frac{\dot{Q}_e}{T_c^{in}}(1 + \frac{\dot{E}_{hp}}{\dot{Q}_e}) \quad (3.6)$$

2. Fixing T_e^{in} and T_c^{in} as constants reduces *Equation 3.6* into $\dot{E}_{hp} = f(\dot{Q}_e)$.
3. Apply piecewise linearization such that $\dot{E}_{hp}$ varies linearly with $\dot{Q}_e$ within predefined bounds $(\dot{Q}_{e,i}^{min}, \dot{Q}_{e,i}^{max})$.

The resultant piecewise linear formulation is,

$$\dot{E}_{hp} = \sum_{i=1}^n \gamma_{0,i} \dot{Q}_{e,i} + Y_{0,i} \nu_{0,i}, \quad Y_i \in [0, 1] \quad (3.7)$$

$$Y_i \dot{Q}_{e,i}^{min} \leq \dot{Q}_{e,i} \leq Y_i \dot{Q}_{e,i}^{max}, \quad \forall i \quad (3.8)$$

$$\sum_{i=1}^n Y_i \leq 1 \quad (3.9)$$

where $\gamma_{0,i}$ and $\nu_{0,i}$ represent constants to be determined, $\dot{Q}_{e,i}^{min}$ and $\dot{Q}_{e,i}^{max}$ denote predefined bounds according to n number of linear pieces. *Equation 3.9* ensures that no more than one linear piece is activated.

4. Use *Equation 3.2* to substitute $\dot{Q}_{e,i}^{max}$ term in *Equation 3.7*.

$$\dot{E}_{hp} = \sum_{i=1}^n \gamma_{1,i} \dot{m}_e T_e^{out} + \gamma_{2,i} \dot{m}_e + Y_i \nu_{0,i}, \quad Y_i \in [0, 1] \quad (3.10)$$

where $\gamma_{1,i}$ and $\gamma_{2,i}$ are constants to be determined.

The constraint in *Equation 3.8* becomes,

$$Y_i \dot{Q}_{e,i}^{min} \leq \dot{m}_e C p_w (T_e^{out} - T_e^{in}) \leq Y_i \dot{Q}_{e,i}^{max}, \quad \forall i \quad (3.11)$$

5. *Equation 3.10* consists of a bilinear term $(\dot{m}_e T_e^{out})$ which could be linearized using the RLT introduced by Sherali et al. [142]. This involved the introduction of additional variables.

- (a) Introduce u and v as variables such that,

$$u = \dot{m}_e + T_e^{out} \quad (3.12)$$

$$v = \dot{m}_e - T_e^{out} \quad (3.13)$$

thus,

$$\dot{m}_e T_e^{out} = \frac{u^2 - v^2}{4} \quad (3.14)$$

- (b) *Equation 3.10* can be expressed entirely in terms of u and v . However it would contain quadratic terms. Piecewise linearization is hence, required again. The following illustrates the final formulation of $\dot{E}_{hp,i}$ in terms of u and v .

$$\begin{aligned} \dot{E}_{hp} = \sum_{i=1}^n \gamma_{3,i} \left\{ \left[\sum_{j=1}^m \gamma_{4,j} u_j + \nu_{1,j} Y_{u,j} \right] + \left[\sum_{k=1}^m \gamma_{5,k} v_k + \nu_{2,k} Y_{v,k} \right] \right\} + \\ \left[Y_i \nu_{0,i} \right], \quad Y_i, Y_{u,j}, Y_{v,j} \in [0, 1] \end{aligned} \quad (3.15)$$

$$Y_i \dot{Q}_{e,i}^{min} \leq \left[\sum_{j=1}^m \gamma_{6,j} u_j + \nu_{3,j} Y_{u,j} \right] + \left[\sum_{k=1}^m \gamma_{7,k} v_k + \nu_{4,k} Y_{v,k} \right] \leq Y_i \dot{Q}_{e,i}^{max}, \quad \forall i \quad (3.16)$$

$$Y_{u,j} u_j^{min} \leq u_j \leq Y_{u,j} u_j^{max}, \quad \forall j \quad (3.17)$$

$$Y_{v,k} v_k^{min} \leq v_k \leq Y_{v,k} v_k^{max}, \quad \forall k \quad (3.18)$$

$$\sum_{i=1}^n Y_i \leq 1, \quad \sum_{j=1}^m Y_{u,j} \leq 1, \quad \sum_{k=1}^m Y_{v,k} \leq 1 \quad (3.19)$$

$$\left[\sum_{j=1}^m Y_{u,j} \right] + \left[\sum_{j=1}^m Y_{v,j} \right] - 2 \left[\sum_{i=1}^n Y_i \right] = 0 \quad (3.20)$$

where all γ s, ν s, and bounds (min, max) are constants to be determined. m and n represent the number of linear pieces defined in each stage. Equation 3.20 ensures that both u and v will be activated and deactivated in tandem.

6. $\dot{E}_{hp}$ could thus, be minimized in terms of u and v . Obtained values will be then used to determine $\dot{m}_e$ and T_e^{out} . A similar approach was used on the condenser side to express $\dot{E}_{hp} = f(\dot{m}_c, T_c^{out})$ linearly. $\dot{m}_c$ however, is kept as a constant as the original model (Equation 3.1) is incapable of handling variations in this variable. Further improvements to the heat pump model is required if this feature is needed.

Figure 3.2 summarizes the abstraction process for the electric heat pump model. The process allows the use of MILP to solve the following problem type with T_e^{in} and T_c^{in} kept as constants.

$$\begin{aligned} & \text{minimize} && \dot{E}_{hp} = f(\dot{m}_e, T_e^{out}) \\ & \text{subject to} && \dot{Q}_{e/c} = \dot{Q}_d \end{aligned}$$

where $\dot{Q}_d$ represents the thermal demand to be met by the heat pump, and $\dot{Q}_e = f(\dot{m}_e, T_e^{out})$. The black-box model of the electric heat pump is illustrated in Figure 3.3. Additional parameters (m, n etc.) are required to be defined separately.

It must be highlighted despite the increased solvability of the above-described heat pump model, there are drawbacks too - the increase in the size of the problem formulation. For every linear and bilinear piece, additional constraints must be

FIGURE 3.2: Summary of the model abstraction process for the electric heat pump.

FIGURE 3.3: Black-box model of the electric heat pump.

written to describe the formulate the problem. The relationship between the number of additional constraints associated with each additional step is shown in the following table.

Type	Number of pieces	Additonal equations	Remarks
Piecewise linearization	$m \geq 2$	$m \times 2$	Equations 3.8, 3.9
RLT	$n \geq 2$	$(n \times 4) + 1$	Equations 3.17, 3.18, 3.19, 3.20

TABLE 3.3: Rate of equation growth with respect to extent of linearization.

As seen in Table 3.3, the number of constraints grows linearly with the number of pieces defined. This relationship indicates that the problem size will increase in a controlled manner, making the MILP formulation suitable for this undertaking.

3.3.1.4 Error analysis

Piecewise linearization is used twice in the abstraction process. The mean-squared-error (MAE) incurred as a result of each linearization step is documented in this section. n and m refers to the number of pieces used to for the linearization of [equation 3.7](#) and [equation 3.14](#) respectively. The error is computed through comparison of the model outputs ($\dot{E}_{hp}$) of the original model ([equation 3.1](#)). The models are trained using data from a centrifugal chiller (reverse heat pump, from the case study discussed in [Chapter 5](#)) for the following illustration. The data contains records of the chiller's electricity consumption and all temperatures and flowrates at the evaporator and condenser.

$n =$	Error ($\Delta\dot{E}_{hp}$, %)
2	5.029
4	0.625
6	0.624

TABLE 3.4: Percentage error incurred with different number of linear pieces, n .

Since there is little improvement in percentage error for $n \geq 4$, [Table 3.5](#) varied m while $n = 4$.

$n = 4, m =$	Error ($\Delta\dot{E}_{hp}$, %)
4	0.753
8	0.490
12	0.422

TABLE 3.5: Percentage error incurred with different number of linear pieces, m while $n = 4$.

Marginal improvement in the output values was observed beyond $m \geq 8$.

The MAE incurred is approximately 0.049% despite applying piecewise linearization twice. It is an indication that the integrity of the original model is preserved. To ensure the reproducibility of the above results, the parameters and coefficient values used in the above example is documented in [Appendix A](#).

FIGURE 3.4: Plot of $\dot{E}_{hp}$ of the original model vs abstracted model.

3.3.2 Cooling tower

3.3.2.1 Description

Cooling towers are often used for heat rejection in cooling systems. They represent the most economical mode of rejecting heat should there be no natural options (water-bodies etc.). *Figure 3.5* shows the schematic of a general cooling tower unit. The objective of this model is to use the variables listed in *Table 3.6* to predict the outlet temperature, make-up water and electricity consumed.

Independent variables	Dependent variables	Constants
$\dot{m}_{ct}^{in}$	T_{ct}^{out}	T_{wb}
T_{ct}^{in}	$\dot{m}_{mu}^{in}$	Cp
$\dot{m}_a^{in}$	$\dot{Q}_{ct}$	T_{mu}^{in}
	$\dot{E}_{ct}$	

TABLE 3.6: Independent variables, dependent variables and constants related to the cooling tower model.

FIGURE 3.5: Schematic of a general cooling tower unit.

3.3.2.2 Selected model

The universal engineering model (UEM) for cooling towers was selected [127]. The model was built using a polynomial approximation of the fundamental laws of mass and energy balance. The model illustrated good performance when compared to the often used of Braun's model. The describing equation for the model is as follows,

$$\varepsilon = \beta_0 + \beta_1 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right] + \beta_2 [T_{ct}^{in} - T_{wb}] + \beta_3 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right]^2 + \beta_4 [T_{ct}^{in} - T_{wb}]^2 + \beta_5 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right] [T_{ct}^{in} - T_{wb}] \quad (3.21)$$

where ε is,

$$\varepsilon = \frac{\dot{m}_{ct}^{in} Cp T_{ct}^{in} + \dot{m}_{mu}^{in} Cp T_{mu}^{in} - \dot{m}_{ct}^{out} Cp T_{ct}^{out}}{\dot{m}_{ct}^{out} Cp (T_{ct}^{in} - T_{wb})} \quad (3.22)$$

To estimate the make-up water required, it is estimated that 1% of the circulating water is evaporated for a 5.6 K change in temperature [143]. An additional 0.27% is added to account for drift and other forms of water losses according to the manufacturer's specifications. Additionally, a calibration constant is added so that this formula can be calibrated with raw data. The resulting formula was,

$$\dot{m}_{mu}^{in} = \alpha \left\{ \left[0.0027 + \left(0.01 \times \frac{T_{ct}^{in} - T_{ct}^{out}}{5.6} \right) \right] \times \dot{m}_{ct}^{in} \right\} \quad (3.23)$$

Finally, the only component which consumes electricity in the cooling tower unit is the fan. A linear relationship between the air flowrate and electricity consumed is assumed. The impact of this assumption on the final objective is small as cooling towers tend to represent a small percentage of electricity consumption of the systems they serve.

$$\dot{E}_{ct} = \gamma \dot{m}_a^{in} \quad (3.24)$$

where γ is a constant to be determined.

3.3.2.3 Model abstraction

Cooling tower models are often complex as they involve heat and mass transfer equations. The following measures are taken to simplify the equations listed in the preceding subsection.

1. Since the value of make-up water is usually very small, it is difficult to get high quality data on its flowrate and temperature. Thus, the assumption that $\dot{m}_{ct}^{in} \approx \dot{m}_{ct}^{out}$ to the simplification of *Equation 3.22*.

$$\varepsilon = \frac{T_{ct}^{in} - T_{ct}^{out}}{T_{ct}^{in} - T_{wb}} \quad (3.25)$$

and

$$\begin{aligned} \frac{T_{ct}^{in} - T_{ct}^{out}}{T_{ct}^{in} - T_{wb}} = & \beta_0 + \beta_1 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right] + \beta_2 \left[T_{ct}^{in} - T_{wb} \right] + \beta_3 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right]^2 + \beta_4 \left[T_{ct}^{in} - T_{wb} \right]^2 + \\ & \beta_5 \left[\frac{\dot{m}_a^{in}}{\dot{m}_{ct}^{in}} \right] \left[T_{ct}^{in} - T_{wb} \right] \end{aligned} \quad (3.26)$$

2. For a cooling tower of n individual units, it is assumed that the fluid flowrate $\dot{m}_{ct}^{in}$ through each tower unit is equally divided. That is to maximize the

cooling area to fluid ratio, and thus ‘free’ cooling. Fixing the total flowrate in the parallel-pumps network configuration, meant that the flowrate through each tower unit is fixed too.

3. *Equation 3.26* is highly non-linear. Since T_{ct}^{out} and $\dot{m}_{ct}^{in}$ had to be fixed due to the heat pump and parallel-pumps network configuration models respectively, T_{ct}^{out} depended only on variables T_{ct}^{in} and $\dot{m}_a^{in}$. Regression is used to reduce the order of the equation, making it simpler for linearization.

$$\Delta T_{ct} = \nu_0 T_{ct}^{in} + \nu_1 \dot{m}_a^{in} + \nu_2 T_{ct}^{in} \dot{m}_a^{in} + \nu_3 \quad (3.27)$$

where $\Delta T_{ct} = T_{ct}^{in} - T_{ct}^{out}$ and ν s represent regression constants to be determined.

The bilinear terms in *Equation 3.27* could be linearized using the RLT.

4. The determination of ΔT_{ct} is important in computing the cooling tower unit’s outlet temperature (T_{ct}^{out}) and the volume of make-up water needed ($\dot{m}_{mu}^{in}$).

Make-up water is not yet considered in the objective function as of yet. It will feature in future problems. Therefore, the above discussed steps enabled the MILP formulation of the following problem.

$$\begin{aligned} &\text{minimize} \quad \dot{E} = f(\dot{m}_a^{in}, T_{ct}^{in}) \\ &\text{subject to} \quad T_{ct}^{out} \leq T_{rq}^{out}, \quad T_{ct}^{out} \geq T_{wb}, \end{aligned}$$

where T_{rq}^{out} is the required outlet temperature as determined by the evaporator/-condenser side of the heat pump (constant). *Figure 3.6* illustrates the black-box model of the cooling tower. *Figure 3.7* summarizes the abstraction process for the cooling tower model.

3.3.2.4 Error analysis

Errors incurred using the RLT is not discussed as results obtained are highly similar to that of the heat pump model. The focus of this subsection is to illustrate the impact of applying regression to simplify the original model (UEM). The R^2

FIGURE 3.6: Black-box model of the cooling tower..

FIGURE 3.7: Summary of the abstraction process for the cooling tower model.

value obtained was about 0.8 indicating a relatively lower level of fitness. *Figure 3.8* illustrates the plot of ΔT_{ct} values using the two models. The cooling tower model was calibrated using data from the case study discussed in *Chapter 5*.

The MAE is high. However, it can be reduced to approximately 10% if regression is applied separately to datasets organized by T_{ct}^{in} into three ranges. This was so as the error was greatest at the extremes.

However, the accuracy of this model did not impact the objective function as the contribution of electricity consumption due to cooling towers is the lowest (5-7 %). Even though the electricity output of this model has poor accuracy, the influence of temperature constraints (T_{wb} etc.) can be of value in terms of guiding the operation of cooling towers in the system. There will be attempts to improve this model in the future. To ensure the reproducibility of the above results, the parameters and coefficient values used in the above example is documented in *Appendix A*.

FIGURE 3.8: Plot of ΔT_{ct} values of the abstracted UEM against UEM.

3.3.3 Pump and network

3.3.3.1 Description

Chilled(evaporator side)/warm(condenser side) water produced by heat pumps is transported via the piping network. The pump(s) and (piping) network are modeled collectively due to their high level of dependence. Two models are developed to capture the essence of the commonly used ‘primary-secondary’ pumping scheme (*Appendix B*) which is critical to understand the cause of inefficiency in the system (‘low- ΔT syndrome’ (*Appendix C*), etc.). These models are designed to output the electricity consumed by pumps and the return fluid temperature while respecting physical and thermodynamic principles/constraints.

The following models will describe the flowrate in two commonly utilized parallel configurations in hydronic systems for thermal energy systems - parallel-pumps and single-pump-parallel network configuration. For the latter, a partial heat exchanger model is embedded; the other side is not modeled because it is out of the scope of the case studies.

3.3.3.2 Selected models

Problem formulations in the literature reviewed are highly simplified, neglecting the pressure and temperature considerations in networks. Hence, the network models used in this section are formulated using analytical models [144]. Consideration of these factors is essential for addressing operation related problems. The following are the four main principles used to build the models.

1. Pump-network system pressure versus flowrate relationship

The flowrate-pressure relationship is illustrated in this part. *Figure 3.9* represents an example of a pump connected to a network system. A network system refers to any combination of network components (pipes, heat exchangers, valves, etc.) which impedes (pressure drop) fluid flow. Generally, the more complex the system is, the higher the pressure drop penalty incurred. Hence, more pumping power is required to move the fluid.

Figure 3.10 illustrates the pressure-flowrate relationship between the pump and the network system. The operating point of the pump-network system will always be the intersection of the two characteristic curves. Adjusting operating parameters (lowering pump speed, closing valve, etc.) will shift both curves, hence the possible operating points are bounded by the solid blue curve (lowest pressure drop case (fully open valves, etc.) for network system curve), solid red curve (pump operating at maximum speed) and the y-axis.

Any pump curve could be represented by a quadratic equation. The general formula for the system curve is,

$$\Delta P_{sys} = \alpha \dot{m}_{sys}^{1.852} \quad (3.28)$$

where ΔP_{sys} , $\dot{m}_{sys}$, α represents pressure, system flowrate and network coefficient respectively, was used to model the network system curve.

2. Pump electricity consumption for a given network.

FIGURE 3.9: Example diagram of a pump-network system.

FIGURE 3.10: Example pump-network system curve.

Manufacturers of pumps often include the plot of electricity consumption versus flowrate of pumps when they operate at their nominal/maximum speeds. This graph is meant to be used alongside with the pressure versus flowrate graph (*Figure 3.10*). To determine the electricity versus flowrate relationship when the speed of the pump is reduced, the efficiency formula recommended by Marchi et al. is used [145]. *Figure 3.11* depicts the curves at maximum RPM (bold) and minimum RPM (dotted) for the lowest pressure requirement of a particular pump-network system configuration.

Estimating the electricity consumed by the pump (E_{pump}) requires the knowledge of the operating point of the pump-network system configuration. For

a given flowrate ($\dot{m}_{sys}$), the electricity consumed by the pump could be approximated as follows,

$$\dot{E}_{pump} = \frac{\Delta P_{op}}{\Delta P_{max} - \Delta P_{min}} \times (\dot{E}_{pump}^{max} - \dot{E}_{pump}^{min}) \quad (3.29)$$

where the maximum and minimum pressures and pump electricity consumption can be determined by the bounded areas shown in *Figures 3.10 and 3.11*.

FIGURE 3.11: Example pump electricity consumption curve.

3. Flowrate in parallel networks

The single-pump-parallel network configuration is commonplace in thermal energy systems, especially for energy distribution. The physics of such a configuration dictates that the pressure in each member of the parallel assembly needs to be identical (*Figure 3.12*). Application of *Equation 3.28* to the depicted setup will reveal that changing the flowrate to any single member (closing a valve etc.) will affect the flowrates in the rest of the branches and the overall system pressure.

4. Temperature mixing of streams

When multiple fluid streams of different temperatures mix, it is important

FIGURE 3.12: Example of single-pump-parallel network diagram.

to determine the temperature of the resultant stream. *Figure 3.13* illustrates three converging streams of different flowrates and temperatures. The objective is to determine the resultant flowrate and temperature of the converged fluid stream. Energy and continuity equations formulae are used to derive *Equations 3.30 and 3.31* [144].

FIGURE 3.13: Example of converging fluid streams of different temperatures.

$$\dot{m}^{out} = \dot{m}_1 + \dot{m}_2 + \dots + \dot{m}_n \quad (3.30)$$

$$T^{out} = \frac{\dot{m}_1 T_1 + \dot{m}_2 T_2 + \dots + \dot{m}_n T_n}{\dot{m}^{out}} \quad (3.31)$$

3.3.3.3 Model abstraction

For simplicity, thermal losses in the networks are not considered as a feature. The methods of determining the electricity consumption of the pump's return/outlet temperatures are common to both types of parallel network configurations.

Network electricity linearization

The objective is to map the shaded areas shown in *Figures 3.10 and 3.11* on to each other. Thus, the goal is to represent $\dot{E}_{pump} = f(\Delta P, \dot{m}_{sys})$ as a single equation. Multi-variate regression is performed, and the following equation ($R^2 \geq 0.98$) was derived.

$$\dot{E}_{pump} = \beta_0 \Delta P_{op} + \beta_1 \dot{m}_{sys} + \beta_2 \quad (3.32)$$

where β s were regression derived constants.

Since the bounds for pressures are defined by the solid blue and red curves (*Figure 3.10*), formulation of the constraints required the application of piecewise linearization on the pump and network system curves.

Piecewise linearization of the network system curve,

$$\Delta P_{sys} = \sum_{i=1}^n \gamma_{0,i} \dot{m}_{sys,i} + \gamma_{1,i} Y_i \quad (3.33)$$

Piecewise linearization of the pump curve at maximum speed.

$$\Delta P_{limit} = \sum_{i=1}^n \nu_{0,i} \dot{m}_{sys,i} + \nu_{1,i} Y_i \quad (3.34)$$

Additional constraints involved.

$$\dot{m}_{sys,i}^{min} \leq \dot{m}_{sys,i} \leq \dot{m}_{sys,i}^{max} \quad \forall i \quad (3.35)$$

$$\sum_{i=1}^n Y_i = 1 \quad (3.36)$$

where γ_S , ν_S , $\dot{m}_{sys,min,i,S}$, $\dot{m}_{sys,max,i,S}$ and Y_i s represent constants, linear limits and binary constants respectively.

Network temperature

Equation 3.31 consist of a fraction and bilinear terms. The RLT is used to linearize the equation [142]. The following steps detailed the process. The objective is to determine the resultant temperature of mixing streams of differing flowrates and temperatures.

1. Fix the total flowrate $\dot{m}^{out} = \sum_{j=1}^m \dot{m}_j$ as a constant, so that the equation becomes purely the sum of bilinear terms as follows,

$$T_{out} = \dot{m}^{out} \left[\sum_{j=1}^m \alpha_j T_j \right] \quad (3.37)$$

where $\sum_{j=1}^m \alpha_j = 1$.

2. Thus, the RLT can be applied. Details were not shown as the process is identical to the heat pump example.

Due to the limitations of *Equation 3.31*, the total flowrate through the both parallel configurations have to be treated as a constants for the models to be linearized.

3.3.3.4 Parallel-pumps network configuration

Figure 3.14 illustrates the pressure and temperature layers of the parallel-pumps network configuration. The method in *Section 3.3.3.3* is used n times to individually determine the electricity consumption of each pump. Since the total flowrate

is a constant, ΔP_{cp} is just a constant to be added on to each of the individual network system curves. This system is not representative of the example shown in *Figure 3.12*. The existence of a pump in each branch means that the pressure difference can be different. However, the pressure difference in the common exit pipe (ΔP_{cp}) is a common addition to all branches.

Determining the resultant outlet temperature of the evaporator network, just requires the application of the method found in *Section 3.3.3.3*. The resultant black-box model of the evaporator network is shown in *Figure 3.15*. *Figure 3.16* summarizes the abstraction process for the parallel-pumps network configuration model.

FIGURE 3.14: Abstracted model of the parallel-pumps network configuration.

FIGURE 3.15: Black-box model of the parallel-pumps network configuration.

FIGURE 3.16: Summary of the abstraction process for the parallel-pumps network configuration model.

3.3.3.5 Single-pump-parallel network configuration

Figure 3.17 illustrates the pressure and temperature layers of the single-pump-parallel network configuration model. The following lists three additional simplifications that are made for this model.

1. If there exist several pumps, every combination is simplified to a single equivalent pump. Pumps working in parallel or series can be represented by a single characteristic pump curve. This curve is then used to estimate the electricity consumed. For example, if there are n pumps in the unit, there are as many equivalent pumps as their series and parallel combinations. The characteristic curves (pressure and electricity versus flowrate respectively) have to be predetermined. One of the many equivalent pumps has to be selected and treated as a constant before the equations of the distribution network model can be determined.
2. The substation (ss) model is not yet developed. Hence, with i^{th} cooling demand ($\dot{Q}_{d,i}$) given as an input constant, the temperature difference at the i^{th} substation ($\Delta T_{ss,i}$) is dependent on the flowrate through the i^{th} substation ($\dot{m}_{ss,i}$) as shown by the following formula.

$$\Delta T_{ss,i} = \frac{\dot{Q}_{d,i}}{\dot{m}_{ss,i} C p_w} \quad (3.38)$$

FIGURE 3.17: Abstracted model of the single-pump-parallel network configuration.

where C_p is the specific heat of the working fluid.

$$T_{ss,i}^{out} = \frac{\dot{Q}_{d,i}}{\dot{m}_{ss,i} C_{p_w}} + T^{in} \quad (3.39)$$

Based on Equation 3.37, the summation of $\alpha_i T_i$ is needed to compute the exit temperature T^{out} (Figure 3.17) of the single-pump-parallel network configuration model. Fixing the total flowrate ($\dot{m}_{sys}$) as a constant will result in the following expression for exit temperature.

$$T^{out} = \sum_{i=1}^m \frac{\dot{Q}_{d,i}}{C_{p_w}} + \alpha_i T_{ss,i}^{in} \quad (3.40)$$

As such, the RLT could be applied for linearization.

To compensate for the lack of substation models, a constraint was imposed on the $\Delta T_{ss,i}$ so that the ‘optimal’ results generated will be fairly realistic.

The constant value $\Delta T_{limit,i}$ was determined manually by considering the specifications of the involved heat exchangers.

$$\frac{\dot{m}_{ss,i} C_{pw}}{\dot{Q}_{d,i}} \geq \frac{1}{\Delta T_{limit,i}} \quad (3.41)$$

3. In reality, there is at least a valve installed at every substation. The valves are used to control flowrates (and hence, cooling supply, etc.) into the substations. Partially closed valves limit flowrates by increasing the pressure difference at the substation ($\Delta T_{ss,i}$). Allowing the flowrate in each parallel member (*Figure 3.17*) to be independent will violate the equation in *Figure 3.12*. However, if valves are to be considered, they could implicitly compensate for the difference in pressure as long as the following inequalities are satisfied. Additionally, the difference between ΔP_i and $\Delta P_{//sys}$ can be used to calculate the extent to which the implied valve is open.

$$\begin{aligned} \Delta P_{//sys} &\geq \Delta P_1 \\ \Delta P_{//sys} &\geq \Delta P_2 \\ &\vdots \\ \Delta P_{//sys} &\geq \Delta P_n \end{aligned} \quad (3.42)$$

Since the objective is to minimize electricity consumed by the pumps, minimization of $\Delta P_{//sys}$ will occur naturally. *Figure 3.18* illustrates the black-box model of the single-pump-parallel network configuration. The abstraction process for this model is summarized in *Figure 3.19*.

FIGURE 3.18: Black box model of the single-pump-parallel network configuration.

FIGURE 3.19: Summary of the abstraction process for the single-pump-parallel network configuration model.

The objective of the network models is to reflect the feasibility of selected flowrate combinations to each substation. Its contribution to the objective function (electricity consumption of pumps) can influence the selection of variables in other models (heat pumps, cooling tower, etc.).

3.3.3.6 Error analysis

First, the relationship between pressure, flowrate, and electricity consumption of a given pump-network system are simplified to a regression model as shown by *Equation 3.32*. The R^2 value for the regression is always greater than 0.98 for all the models evaluated. The average MAE error is under 10% if a single regression is performed. Using the parallel pumps network configuration model as an example, pump electricity consumption values obtained using the graphical method and the simplified regression methods are plotted in *Figure 3.20*. From the plot, it could be seen that the error is highest at low electricity consumption. When regression is done separately for high and low flow ranges, the error can be kept under 5% for all models.

The next source of error is attributed to the temperature estimation using the RLT. For the ease of coding, the number of piecewise linear steps used are the same as

FIGURE 3.20: Plot of $\dot{E}_{pump}$ of the graphical method and regression model.

the value used for the heat pump model. The error is found to be under 1%. To ensure the reproducibility of the above results, the parameters and coefficient values used in the above example is documented in *Appendix A*.

3.3.4 Water-to-air heat exchanger

3.3.4.1 Description

WAHXs are typically known as air towers, used for heat rejection/absorption from the environment in thermal energy systems. They are much simpler compared to cooling towers as only sensible heat transfer is involved. *Figure 3.21* shows the schematic of a typical WAHX unit. The objective of this model is to use the variables listed in *Table 3.7* to predict the outlet water temperature and electricity consumed.

FIGURE 3.21: Schematic of a general water-to-air heat exchanger.

Independent variables	Dependent variables	Constants
$\dot{m}_a$	$\dot{E}_{WAHX}$	T_a^{in}
$\dot{m}_w$	T_w^{out}	
T_w^{in}	T_a^{out}	

TABLE 3.7: Independent variables, dependent variables and constants related to the WAHX model.

3.3.4.2 Selected model

To model the WAHX, the LMTD equation that governs counterflow heat exchangers is used alongside SFEEs. This is a theoretical model, not based on any existing hardware, hence only utilizes analytical equations. With the addition of a correction factor (Cf), the LMTD equation can be used to model various crossflow heat exchangers accurately. For illustration purposes, we assume that the WAHX functions as an air-cooled condenser for a heat pump in cooling mode. The equations used for modeling are as follows,

$$\dot{Q}_{WAHX} = Cf \times UA \left[\frac{(T_a^{in} - T_w^{out}) - (T_a^{out} - T_w^{in})}{\ln \frac{(T_a^{in} - T_w^{out})}{(T_a^{out} - T_w^{in})}} \right] \quad (3.43)$$

$$\dot{Q}_{WAHX} = \dot{m}_w \times Cp_w \times (T_w^{in} - T_w^{out}) \quad (3.44)$$

$$\dot{Q}_{WAHX} = \dot{m}_a \times Cp_a \times (T_a^{out} - T_{amb}) \quad (3.45)$$

where $\dot{Q}_{WAHX}$ is the heat rejected into the environment by the WAHX. To estimate the electricity consumed by the fans, the following linear equation is assumed. The impact of this assumption on the final objective function is small as fans make up for only a very small percentage of the electricity consumption of the systems they serve.

$$\dot{E}_{WAHX} = \alpha_0 \dot{m}_a \quad (3.46)$$

where α_0 is a constant to be determined.

3.3.4.3 Model abstraction

The LMTD equation is relatively complex as it involves logarithmic and fractional terms. The following measures are taken to simplify the equations listed in the preceding subsection.

1. $\dot{Q}_{WAHX}$ can be expressed directly in terms of T_w^{out} , $\dot{m}_w$ and $\dot{m}_a$ through the manipulation of *Equations 3.43 to 3.45*. Since $T_a^{in} = T_{amb}$, T_a^{in} also becomes a constant.
2. For all manufacturer's documentation on similar WAHXs, there always exists a nominal approach temperature (T_{app}) between the cold and hot streams passing through the heat exchanger. This minimum temperature value exists to ensure that there is always a temperature gradient for thermal exchange. For simplification purposes, this value is treated as a constant.

$$T_{app} = T_{amb} - T_w^{out} \quad (3.47)$$

3. Discretizing $\dot{m}_w$, permits $\dot{Q}$ to be a single-valued function of $\dot{m}_a$. Regression can then be used to linearize this relationship. This also enables $\dot{E}_{WAHX}$ to directly related to $\dot{Q}_{WAHX}$ through equating *Equations 3.46 and 3.48*.

$$\dot{Q}_{WAHX} = \beta_0 \dot{m}_a \quad (3.48)$$

where β_0 is a constant to be determined.

The purpose of the abstraction process for the WAHX is to expressed as a MILP in the following manner,

$$\begin{aligned} & \text{minimize} && \dot{E}_{WAHX} = f(\dot{m}_a) \\ & \text{subject to} && \dot{Q}_{WAHX} \geq \dot{Q}_{rq}, \end{aligned}$$

where $\dot{Q}_{rq}$ is the required heat to be rejected by the heat pump into the environment. *Figure 3.22* illustrates the black-box model of the WAHX. The abstraction process for the WAHX is summarized in *Figure 3.23*.

FIGURE 3.22: Black-box model of the water-to-air heat exchanger.

FIGURE 3.23: Summary of the abstraction process for the water-to-air heat exchanger model.

3.3.4.4 Error analysis

Figure 3.24 shows the plots of the predicted $\dot{Q}_{WAHX}$ values of the abstracted WAHX and analytical-equation-based models. The R^2 values obtained were consistently very high (≥ 0.98) for the predefined WAHX parameters set for the case study. The MAE obtained is slightly under 10%. This is indicative of a good approximation made by the linear equation. To ensure the reproducibility of the above results, the parameters and coefficient values used in the above example is documented in *Appendix A*.

FIGURE 3.24: Plot of $\dot{Q}_{WAHX}$ of the analytical method and regression model.

3.3.5 Other models

3.3.5.1 Description

This subsection details the remaining models that are required for the case studies. Models listed need little to no abstraction - they are either extracted directly from literature or just discretized, hence not discussed in as much detail as those above.

3.3.5.2 Building integrated photovoltaics

BIPVs are solar PVs which are integrated onto the building, in the form of roofs and facades. They function as an alternative source of electrical power from the grid. The objective of this model is to use ambient conditions to determine the useful electrical energy generated. *Table 3.8* documents the variables and constants related to this model.

The usable electricity ($\dot{E}_{PV}$) produced by the BIPVs is essentially not tuneable as the independent variables of this model is only represented by ambient conditions (parameters). Hence, there is no need for model abstraction. The equation-based BIPV model proposed by Neuhaus et al. is used in this thesis [135]. Finally, the case study (*Chapter 4*) in this thesis uses the same dataset as in the paper, hence, the errors incurred are identical, averaging about 6.2%. *Equation 3.49* describes the BIPV model, which was selected. The black-box model of the BIPV model is shown in *Figure 3.25* details the resulting black-box model of the BIPV.

Independent variables	Dependent variables	Constants
$G_{i\omega}$	$\dot{E}_{PV}$	PV_{sf}
T_{amb}	T_{PV}	$\eta_{PV,i}$
		$\eta_{INV,i}$
		$loss_{mm}$
		$loss_{OHM}$
		$Ktemp$

TABLE 3.8: Independent variables, dependent variables and constants related to the BIPV model.

$$\begin{aligned} \dot{E}_{PV} = & \left[PV_{sf} G_{i\omega} \eta_{PV} \eta_{INV} \times (1 - loss_{mm}) \times (1 - loss_{OHM}) \right] \\ & \times (1 + (T_{PV} - T_{amb}) \times Ktemp) \end{aligned} \quad (3.49)$$

3.3.5.3 Electricity storage system

Due to the lack of data, a simple battery model is assumed for use as an electricity storage system (ESS) for estimating the potential cost savings from storing grid electricity when the unit cost is favorable [138]. An efficiency term (η_{ESS}) is used to penalize the SOC ($\dot{E}_{ESS}$) each time the ESS is charged. This means that the input electrical energy in the previous time-period (t) is always more than for use in the

FIGURE 3.25: Black-box model of the BIPV.

current time-period ($t + 1$). To incorporate the effect of diminishing efficiencies as the SOC increases, values of η_{ESS} in Equation 3.50 is discretized. The variables and constants of the ESS model is documented in Table 3.9 and Figure 3.26 summarizes the corresponding black-box model.

Independent variables	Dependent variables	Constants
$\dot{E}_{ESS,t}^{in}$	$\dot{E}_{ESS,t+1}^{out}$	η_{ESS}

TABLE 3.9: Independent variables, dependent variables and constants related to the ESS model.

$$\dot{E}_{ESS,t+1}^{out} = \eta_{ESS} \dot{E}_{ESS,t}^{in} \quad (3.50)$$

FIGURE 3.26: Black-box model of the ESS.

3.3.5.4 Ground heat exchangers

Ground heat exchangers at the building-level typically exist as borehole heat exchangers. These heat exchangers facilitate thermal exchange between the working fluid of heat pumps and the ground. The working fluid used is typically water. Two models are addressed in this subsection - the heat exchanger model and the ground temperature model. Table 3.10 shows the variables and constants of the

GHX model. For illustration purposes, only the case where the working fluid has to be cooled down by the ground, i.e., a heat pump in cooling mode, is considered.

Independent variables	Dependent variables	Constants
$\dot{m}_{w,t}$	$T_{g,t}$	$T_{g,t+1}$
$T_{w,t}^{in}$		$T_{w,t}^{out}$

TABLE 3.10: Independent variables, dependent variables and constants related to the GHX model.

Heat exchanger model

Similar to the WAHX model, the LMTD equation is used to model the thermal interactions in the heat exchanger, with the only difference being the assumption that for every time-period (t), the ground temperature remains invariant (T_g). T_g is only allowed to vary between time-periods. Through this assumption, it is possible to model the GHE as though the fluid stream is having thermal exchange with a surface of constant temperature.

Equation 3.51 details the LMTD formula used for the GHE. By Equations 3.51 and 3.52, $\dot{Q}_t$ can be expressed as a single-valued function of $T_{w,t}^{out}$ for fixed values of $\dot{m}_{w,t}$ and $T_{g,t}$. This enables the estimation of the return temperature value to the heat pump, which is essential for the calculation of the *COP*.

$$\dot{Q}_t = Cf \times UA \left[\frac{(T_{g,t} - T_{w,t}^{out}) - (T_{g,t} - T_{w,t}^{in})}{\ln \frac{(T_{g,t} - T_{w,t}^{out})}{(T_{g,t} - T_{w,t}^{in})}} \right] \quad (3.51)$$

$$\dot{Q}_t = \dot{m}_{w,t} \times Cp_{w,t} \times (T_{w,t}^{in} - T_{w,t}^{out}) \quad (3.52)$$

Ground temperature model

To approximate the variation of T_g with the amount of thermal energy rejected, curve fitting methods are used. The equations used are deducted from the shape of the plots which are obtained from the initial tests performed on the system. The shape of the curves is consistent with those found in [131]. There are two modes to this model - active and passive, where there is ongoing thermal exchange with the heat pumps and left to recover to its original temperature respectively. Equation

3.53 describes the gradual heating of the ground when heat is rejected. Equation 3.54 describes the cooling of the ground when it is not involved in any thermal exchange over a predefined time-period, t . Similar equations but reflected over the abscissa are used to describe the temperature variation of the ground when it is used as a heat source.

$$T_{g,t} = \alpha_0 \ln \left[\left(\sum_{t=1}^m \dot{Q}_t \right) + 1 \right] + T_{g,init} \quad (3.53)$$

$$\Theta_{t+1} = \alpha_0 e^{(T_{g,t} - T_{g,init})^{\alpha_1}} + \alpha_2 \quad (3.54)$$

where $\Theta_t = T_{g,t} - T_{g,init}$.

Combining both the sub-models

To ensure compatibility with MILP, $T_{g,t}$ is discretized for each cumulative range of $\sum_{t=1}^m \dot{Q}_t$. These provisions for the temperature of the ground to varying in accordance with the total amount of thermal exchange which has already occurred. Hence, for each range of $\sum_{t=1}^m \dot{Q}_t$, $T_{g,t}$ is a constant value which is used to calculate for $T_{w,t}^{in}$. Naturally, with more discretized values, the accuracy of the model is increased correspondingly. Figure 3.27 summarizes the GHX black-box model.

FIGURE 3.27: Black-box model of the GHX.

3.3.5.5 Thermal energy storage

A two-layer water tank with fully mixed layers is assumed for this TES model. A loss coefficient, k_{loss} is incorporated to estimate the amount of usable stored thermal energy for the subsequent time-period $(t + 1)$. The schematic of a two-layer TEX

tank is shown in *Figure 3.28*, and the corresponding variables and constants are detailed in *Figure 3.11*.

FIGURE 3.28: Schematic of a two-layer TES tank.

Independent variables	Dependent variables	Constants
T_{hot}^{in}	$T_{s,hot}$	V^{max}
T_{cold}^{in}	$T_{s,cold}$	
$\dot{m}_1$	V_{cold}	
$\dot{m}_2$	T_{cold}^{out}	
	T_{hot}^{out}	

TABLE 3.11: Independent variables, dependent variables and constants related to the TES model.

For simplicity, the TES model can only operate in either charging or discharging mode only. For illustration purposes, only equations relating to cold water charging and discharging are considered in the following equations. Hot water charging only involves exchanging the corresponding hot and cold variables and is not discussed. The subscripts denote the corresponding time-periods (t) they represent. The cold water charging or hot water discharging mode equations are as follows.

$$T_{s,cold,t+1} = (1 + k_{loss}) \times \frac{T_{cold,t}^{in} \dot{m}_{1,t} + T_{s,cold,t} \frac{V_{cold,t}}{t}}{\dot{m}_{1,t} + \frac{V_{cold,t}}{t}} \quad (3.55)$$

$$V_{cold,t+1} = \dot{m}_{1,t} + V_{cold,t} \quad (3.56)$$

$$\dot{m}_{2,t} = 0 \quad (3.57)$$

$$T_{hot,t}^{out} = T_{s,hot,t} \quad (3.58)$$

$$T_{s,hot,t+1} = k_{loss} \times T_{s,hot,t} \quad (3.59)$$

Since the objective of including a TES model into the optimization framework is just to prove an additional feature of the optimization methodology proposed in *Chapter 6*, a simplified version of the TES model used by Schütz et al. is deployed [141]. However, instead of fixing the volume in each layer as constants, the temperature is discretized. Additionally, by fixing the value of T_{hot}^{in} as a constant and letting $T_{hot}^{in} = T_{hot}^{out}$ to reduce calculations on the hot-side of the TES, the above equations can be simplified as follows,

1. Cold water charging mode

$$\dot{Q}_{cold,t}^{in} = \dot{m}_{1,t} \times Cp_w \times (T_{hot}^{out} - T_{cold,t}^{in}) \quad (3.60)$$

$$\dot{Q}_{s,cold,t+1} = \dot{Q}_{cold,t}^{in} + \dot{Q}_{s,cold,t} \quad (3.61)$$

$$\dot{m}_{2,t} = 0 \quad (3.62)$$

2. Cold water discharging mode

$$\dot{Q}_{cold,t}^{out} = \dot{m}_{2,t} \times Cp_w \times (T_{hot}^{out} - T_{cold,t}^{out}) \quad (3.63)$$

$$\dot{Q}_{s,cold,t+1} = \dot{Q}_{cold,t}^{out} - \dot{Q}_{s,cold,t} \quad (3.64)$$

$$\dot{m}_{1,t} = 0 \quad (3.65)$$

Hence, by discretizing the values which T_{cold} can assume, $\dot{Q}_{cold}$ can be expressed solely as a function of $\dot{m}_{cold}$, making the equation linear and compatible with the MILP format. The black-box model of the TES is shown in *Figure 3.29*.

FIGURE 3.29: Black-box model of the TES.

3.3.6 Summary

The abstraction process is critical in increasing the solvability of the optimization problem. It enabled models of higher complexity to be optimized with more realistic results generated. This aspect has been missing from optimization problems related to urban energy systems. The benefit of model abstraction is clearly highlighted in *Chapter 4*.

Despite various attempts to linearize the models, however, there are certain variables that had to be left out (treated as constants) in the abstraction process. Thus, there is a need for other means of dealing with such variables, if required (*Chapter 5*). Errors incurred in the abstraction process are generally low, thereby indicating the preservation of the integrity of the original models.

Three main techniques are deployed in this chapter, piecewise linearization, treatment of bilinear variables using RLT and the simplification of analytical equations using regression. It must be highlighted however, that the first two techniques come at a cost of enlarging the size of the problem formulation.

Chapter 4

Holistic optimization using abstracted models

4.1 Overview

Two essential criteria have to be met for the results of optimization studies on the operation of urban energy systems to be useful - the expression of decision variables which are tuneable, and the modeling of interactions among the critical components of the system. The latter criterion ensures that the solution space of the problem is thoroughly explored, i.e, optimized holistically. Holistic optimization is paramount, given that components within the system are highly interdependent.

The judicious use of abstraction techniques on carefully selected component-level models is used to achieve the required criteria (*Chapter 3*). The importance of these criteria, especially for operation optimization is highlighted through the implementation on a case study based on an existing building-level GCHP system, which is an example of an urban energy system. In this chapter, the limitations of the existing literature on optimizing the operations of the GCHP system is first, briefly highlighted. Subsequently, a detailed description of the case study and its associated limitations is presented. The naturally accompanying problem formulation is then, shown in *Section 4.5*, before concluding with a discussion on the insights and limitations gained from this optimization study. This piece of

¹The work in this chapter is under review in [146]

work has just been submitted to the *Energy and Buildings* journal and is currently under review [146].

4.2 Introduction

Enhanced efficiency due to lower compressor-lift is the primary reason for the increasing popularity of GCHP systems [147, 148]. After a certain depth, the temperature of the ground is relatively invariant to ambient conditions, making it an ideal heat source or sink depending on heating or cooling requirements [149]. Given that space conditioning in buildings account for up to 13% of the global final energy use, any attempt to reduce this statistic could not be more welcomed [150]. The potential of GCHP systems in reality, however, is often not fully realized owing to the difference in design and operating conditions [151]. The slow dissipation of thermal energy in the ground is a consequence of the inferior thermal conductivity of the soil. The outcome is the gradual degradation of the temperature and performance of the ground as a heat source or sink, which threatens to negate the only advantage of GCHPs. These issues are much more pronounced in regions dominated by either heating or cooling, as the ground is hardly left to fallow.

Rigid control strategies based on pre-defined setpoints, or which are only concerned with maximizing efficiency at the component-level exacerbate these problems [152]. These measures disregard the cascading effect on the system level, thereby inhibiting the ability of the GCHP system to adapt appropriately under less desirable operating circumstances. Therefore, the focus of the current work is to comprehensively explore the solution space mapped by tuneable variables of the GCHP system using mathematical optimization techniques. This permits insights into possible means of improving the system-level efficiency without the incurrence of high monetary costs, to be gained.

4.2.1 Ground-coupled heat pump (GCHP) system

A GCHP system leverages on thermal exchange with the ground for efficiency gains. Regardless of the season, comfortable room temperature is typically closer to the ground rather than the ambient air temperature. The smaller temperature

difference reduces the mechanical load on the compressor of the heat pump, which translates into a superior efficiency when compared to traditional systems.

Figure 4.1 illustrates a GCHP system serving the *architectures dynamiques re-configurables pour systèmes embarqués autonomes mobiles* (ADREAM) building of the *Laboratoire d'analyse et d'architecture des systèmes - Centre national de la recherche scientifique* (LAAS-CNRS) laboratory. The ADREAM building hosts an experimental platform for optimized energy networks, BIPV research, and smart grids, with the purpose of simulating zero-energy strategies according to the definitions of zero-energy buildings (ZEB) [153].

FIGURE 4.1: Layout of a GCHP system serving a laboratory.

Bore-hole heat exchangers are commonly used in systems of such scale to execute the thermal exchange with the ground. In cooling mode, hot water from the condensers of the heat pumps is circulated and cooled down by the ground. The reverse is true during heating mode. These heat exchangers usually are installed in parallel and drilled to a depth deep enough so that the ground temperature remains relatively uniform in spite of ambient conditions.

4.2.2 Objectives

Two essential criteria have to be met for the results of the optimization study to be useful - the expression of decision variables which are tuneable in reality, and the modeling of interactions between the critical components of the GCHP system.

The same cooling or heating demand could be fulfilled by countless combinations of component setpoints, each with a different impact on global system-level efficiency. Non-linearities inherent within the governing equations of the component models (heat pump, pump, ground heat exchanger) further compounds the complexity of the ensuing optimization problem. Categorical denial of existent scenarios whereby a compromise on the efficiencies of some components of the GCHP system, for enhanced system-level efficiency prunes the already restricted solution space of the problem through the introduction of unnecessary constraints. This explains why component-level optimization is less impactful than the holistic approach for operation purposes.

As a pre-requisite to the formulation of the optimization problem, models that appropriately express the workings of each component of the GCHP system as a function of tuneable variables (flowrate, temperature setpoint, pressure) are first identified. These models are then abstracted in a fashion whereby the resultant formulation is compatible with the MILP format (*Chapter 3*). That requires the prudent exploitation of case-study specific information for balancing of model fidelity and compatibility for optimization.

This optimization strategy is then applied to several scenarios of a case study based on an existing GCHP system from the ADREAM building in Toulouse. Throughout the four scenarios defined, a single component is progressively added to the optimization problem before investigating its impact on either of the defined objective functions - total electricity consumption or operating cost. Through the results of the case study, the merits of modeling the tight-coupling amongst the GCHP components before performing optimization holistically is explicitly observed. The findings suggest that hybridizing the GCHP system with a theoretical WAHX as an alternative to thermal exchange with the ground could result in electricity and cost savings of up to 12.7% and 35% over a year.

4.2.3 State of the art

Designing a GCHP system using the popular rule-based methods yield errors ranging anywhere from -21 % to 167%, primarily where the sizing of GHE is concerned [154, 155]. Optimization work on the design of GCHP systems attempts to bridge this gap by utilizing models with higher precision to match the required cooling

or heating demands [156, 157]. Such studies try to determine the optimal configuration of equipment sizing such as the heat pump, piping network, with most of the attention paid to the design of GHEs [158, 159]. Where complex multi-energy systems involving GCHPs are concerned, meta-heuristics are often found to be deployed in tandem with simulation-based software such as TRNSYS [160–162].

The deviation between the optimal design and performance will always exist in reality; as it is inevitable to make assumptions about operating conditions [163]. Optimization of GCHP operation entails a different set of requirements - models with higher fidelity and a problem formulation that has reasonable convergence speed [25, 130]. Assumptions such as constant operating coefficients of performance (COP) and temperatures of the heat pumps or ground, while they greatly simplify the optimization problem, serve little purpose for operation. Polynomial approximations of complex component models coupled with more robust optimization techniques offer a rational compromise between modeling accuracy and computational efficiency, hence they are often deployed in model predictive control algorithms.

It is well established that evaporating and condensing temperatures have a strong influence on the operating COP s of heat pumps. Under specific scenarios, electricity savings of up to 28% could be achieved with the adjustments in space conditioning set-point temperatures [152]. Erosion of the gains in COP s is often observed in GCHP systems due to the degradation of ground temperatures [151]. Hybridization of GCHP systems with alternative thermal exchange options, such as cooling towers, alleviates the burden on the ground and permits temperature recovery [164]. Various control strategies ranging from rule-based to the use of artificial neural networks (ANN) methods of toggling between GHEs and the available alternatives resulted in significant COP improvements for these systems [165, 166].

GCHP systems, just as heating, ventilation, and air-conditioning (HVAC) systems are also comprised of several energy-consuming components such as heat pumps, pumps, and heat exchangers, working in tandem. It is not inconceivable for ancillary components to have a significant influence on system-level energy performance. Parallels had to be drawn from studies concerning the holistic optimization of the operation of closely-related systems due to the lack thereof, on GCHP systems [130]. For chiller systems serving commercial buildings, optimization involving ancillaries enabled additional energy savings of 6.5% [167]. The uncovering of

counter-intuitive operating strategies which could only have resulted through the modeling of the tight-coupling between the main components and ancillaries of the system are clearly illustrated in [166].

It becomes evident from the review that a gap exists where the optimization of the operation of GCHP systems at the system-level is concerned. The few related studies prioritized the optimal performance of heat pumps for a given thermal load, neglecting the impact of ancillaries [130]. Hence, it is natural to assume that as the complexity of systems increases, the interdependencies between components will naturally be more pronounced, further reinforcing the need for holistic optimization.

4.3 Description of the chosen case study

The case study described in this chapter is based on a functioning GCHP system serving a laboratory in Toulouse (*Figure 4.1*). This laboratory is part of the ADREAM project which focuses on the collective optimization of smart-grids, BIPV, HVAC, and ambient cyber-physical systems [153]. Simulations studies on the GCHP system of interest have since been conducted to identify areas for energy savings manually [168]. The current work is an extension of these studies through the lens of mathematical optimization performed at the system-level.

Analysis of data collected through the numerous sensors installed around the laboratory revealed two key areas to address for improving the energy performance of the GCHP system - improving the operation of the hydronic network and the ground temperatures. Inferior evaporating and condensing temperatures in the winter and summer respectively appeared to adequately explain the deviation between the theoretical and actual efficiencies of the heat pumps. This suggests that GHEs are likely to have been undersized. Additionally, the rule-based operation inhibited the adaptability of the system for less-than-ideal scenarios. Therefore, the case-study scenarios defined in this chapter attempt to utilize potential improvements in operating practices for enhanced energy performance. The abstracted models of the system components are deployed for this undertaking (*Chapter 3*).

Figure 4.2 illustrates the GCHP system serving the laboratory. It comprises of three identical heat pumps serving a total of five zones of various usage (office,

server rooms, laboratories). Depending on the season, the 18 borehole heat exchangers function as either a heat sink or source. The entire GCHP system could be powered by electricity from any combination of the three sources - grid, battery, or directly from solar photovoltaics (*Figure 4.1*). The size of the components considered in the GCHP system is documented in *Table 4.1*.

Description	Nominal capacity	Quantity	Remarks
Heat pump (cooling mode)	45(kW)	3	
Heat pump (heating mode)	50(kW)	—	Same heat pump.
Evaporator pump	10.1896 — 10.3841(m^3/h)	3	Depending on the number of concurrent pumps running. Constant flowrate. Electricity consumption is approximately 0.85(kWh)
Condenser pump	6.0366 — 6.2258(m^3/h)	3	Depending on the number of concurrent pumps running. Constant flowrate. Electricity consumption is approximately 0.65(kWh)
Distribution pump	43(m^3/h), 15.8938(mmH ₂ O)	1	Maximum flowrate and pressure values. Variable flowrate. Maximum electricity consumption is 1.5(kWh).
Ground heat exchanger	500(kW)	9	A system of borehole heat exchangers.
Water-to-air heat exchanger	170(kW)	1	

TABLE 4.1: Size of components considered in the GCHP system.

In the following two subsections, the case-study scenarios are defined to address the two identified issues and discuss the management of the input data used. These lay the foundation for selecting the appropriate models and eventually formulate the optimization problem, which will be discussed in greater detail in *Section 4.5*.

4.3.1 Description of the chosen case-study scenarios

With the improvement of the hydronic network and ground temperature performances listed as primary objectives, four case-study scenarios were defined. These scenarios are chosen to progressively optimize the energy performance of the GCHP system so that the final result will be better assimilated. Optimization, when performed at the system-level, tend to lead to results that are not easily appreciable due to the amalgamation of non-linearities in, and interactions among sub-systems.

FIGURE 4.2: Schematic of the GCHP system serving the laboratory.

An alternative thermal exchange option had to be added to the system to reduce the degradation of the ground temperatures (*Figure 4.3*). For that, a water-to-air heat exchanger was chosen to enable the heat pumps to interact with the ambient air, thermally. Consequently, avenues were explored to justify the added monetary investment through the inclusion of battery operation and costs objectives to the optimization problem. Hence, the final model had to include heat pumps (HP), evaporator and condenser pumps (EP, CP), distribution pumps (DP), GHEs, WAHX, PV, grid electricity (GE) and an ESS.

Three base (*bc*) and four optimization cases (*opt*) form the basis of the case-study scenarios. *Table 4.2* documents the base and optimization cases at the component level. *Table 4.3* describes the objective of each case-study scenario defined in this chapter.

FIGURE 4.3: Schematic of a hybrid GCHP system.

	HP	EP	CP	DP	GHE	WAHX	ESS	OF
<i>bc1</i>	F	F	F	CS	F	NA	NA	NA
<i>bc2</i>	F	F	F	VS	F	NA	NA	NA
<i>bc3</i>	F	F	F	VS	NA	NA	ES	NA
<i>opt1</i>	F	F	F	O	F	NA	NA	$\dot{E}$
<i>opt2</i>	F	F	F	VS	F	NA	O	$C_{\dot{E}}$
<i>opt3</i>	O	F	F	O	O	O	O	$\dot{E}$
<i>opt4</i>	O	F	F	O	O	O	O	$C_{\dot{E}}$

Legend: *F* - fixed, *O* - optimized, *CS* - constant speed, *VS* - variable speed, *ES* - extra solar, stored, *NA* - not applicable, *OF* - objective function.

TABLE 4.2: Base and optimization cases used in case studies.

4.3.2 Management of input data

Ambient and demand conditions are the input data to the optimization problem. For the purpose of the case study, the two following simplifications were made.

1. Aggregation of rooms to zones. The laboratory comprises of 36 rooms which are summarized into five zones, grouped by the similarity of their demand profiles.
2. Usage of typical days to approximate monthly conditions. Every month of the year is represented by a single 24-hour day thermal demand and ambient condition profile.

The cumulative thermal demand of the chosen days used for each month is documented in *Figure 4.4*. The ambient conditions (T_{amb} and $G_{i\omega}$) were then used to calculate the available electricity generated using the BIPV model, as shown in *Figure 4.5*. These simplifications drastically reduce the resolution time required for the solvers. Since the main purpose of this chapter is to illustrate the benefits

No.	Objective function	Description
1	$\dot{E}$	<i>bc1</i> vs <i>bc2</i> vs <i>opt1</i> . Comparison of the energy performance of distribution pumps under three operating strategies - constant speed, variable speed, and when the setpoint pressure is optimized for a given demand.
2	$C_{\dot{E}}$	<i>bc3</i> vs <i>opt2</i> . Cost comparison between the optimized battery operation considering hourly electricity pricing as opposed storing electricity only when there is excess from the BIPVs.
3	$\dot{E}$	<i>bc3</i> vs <i>opt3</i> . Hybridization of the GCHP system through the addition of a theoretical water-to-air heat exchanger. Comparison of the energy performance of the optimized hybrid system against the current one.
4	$\dot{E}$ and $C_{\dot{E}}$	<i>opt3</i> vs <i>opt4</i> . Cost and energy comparison of the theoretical hybrid GCHP system when holistically optimized for different objectives.

TABLE 4.3: Description of the case-study scenarios.

of performing holistic optimization on the GCHP system, such approximations are still applicable as they do not mask the important trends (*Section 4.6*). Hourly electricity pricing data was also used as input for the case study. There are six pricing tiers, which differ according to the month of the year and the hour of the day (*Figure 4.6*). The detailed input data used for the case study is documented in *Appendix D*.

4.4 Model selection and abstraction

Table 4.4 documents the list of the parameters and the variable bounds for the abstracted component-level models which are used for the case study. The operating cost can be easily determined by multiplying the hourly electricity consumption by the specific unit cost of electricity for the given hour ($\dot{E}_{ele.rate}$). All model variables which were held constant for the sake of linearization will be addressed in *Section 4.6*.

FIGURE 4.4: Cumulative thermal demand in a typical day per month.

4.5 Problem formulation

This section deals with the mathematical formulation of the optimization problem. Inequalities are introduced to enable the component-level models to interact. Depending on the optimization cases defined in *Table 4.2* the objective function could either be the minimization of total operating cost ($C_{\dot{E}}$) or electricity consumption ($\dot{E}$).

In the following two subsections, the treatment of parameters and variables of the GCHP system are first determined before the formulation of the optimization problem. Subsequently, the error incurred in the models is discussed, before simulating the defined base cases.

4.5.1 Parameters and variables

The fidelity of the component models selected enables a degree of freedom higher than required for the GCHP system. Simplification of the problem formulation is done by only considering the tuneable variables of the system. *Table 4.5* details

FIGURE 4.5: Cumulative solar power generated in a typical day per month.

the treatment of the model variables which were held constant for the sake of linearization. This, however, is only specific to the case study.

Three identical heat pumps, coupled with non-adjustable flowrates on the evaporator and condenser sides allow the further simplification of the optimization problem by exploiting the equal-load distribution operating strategy (ELD) [169]. The exploitation of the ELD strategy and the treatment of the temporary parameters enabled the optimization problem to be reduced entirely to a MILP. Variables and parameters of a single time-step (1-hour), before the abstraction procedures, are detailed in *Table 4.6*.

4.5.2 Mathematical formulation

In the case-study scenarios, the GCHP system is either optimized with respect to the total electricity consumed ($\dot{E}$) or total operating cost ($C_{\dot{E}}$). The two objective functions are:

FIGURE 4.6: Hourly electricity pricing structure across the year.

$$\begin{aligned}
 \text{minimize } \dot{E} = & \sum_{t=1}^m \left[\dot{E}_{WAHX,t} + \dot{E}_{dist,pump,t} + \sum_i^3 \dot{E}_{e,pump,t} + \sum_i^3 \dot{E}_{c,pump,t} + \right. \\
 & \left. \sum_{i=1}^3 \dot{E}_{hp,i,t} + \sum_{i=1}^{pwl} (1 - \eta_{ESS,i}) + \dot{E}_{ESS,i,t}^{in} \right]
 \end{aligned} \tag{4.1}$$

Component	Equation	Coefficients	Variable bounds	Remarks
Heat pump	3.1	$\beta_0 = 0.0264$ $\beta_1 = -2.7306$	$0 \leq \dot{Q}_e \leq 45$ $25 \leq T_c^{in} \leq 30$	Function of T_{db} , T_g and discretized, if in cooling mode.
	3.2	$\beta_2 = 0.3177$	$2 \leq T_e^{out} \leq 8$	Function of T_{db} , T_g and discretized, if in heating mode.
	3.4	$\alpha_0 = 1.1018$		
Evaporator pump-network			$10.1896 \leq \dot{m}_e \leq 10.3841$	Constant speed, 3 fixed flowrates, same electricity consumption.
Condenser pump-network			$6.0366 \leq \dot{m}_e \leq 6.2258$	Constant speed, 3 fixed flowrates, same electricity consumption.
Distribution pump-network	3.28	$\alpha = 0.0049$	$0 \leq \dot{m}_{nwk} \leq 43$	Zone 1, cooling mode.
	3.32	$\alpha = 0.0817$ $\alpha = 0.1392$ $\alpha = 0.0239$ $\alpha = 0.0543$ $\alpha = 0.5969$ $\alpha = 0.4328$ $\alpha = 0.1839$ $\alpha = 0.0439$ $\beta_0 = 0.0266$ $\beta_1 = 0.0710$ $\beta_2 = 0.1331$ $\beta_0 = 0.0229$ $\beta_1 = 0.0789$ $\beta_2 = 0.0946$	$0 \leq \Delta P_{nwk} \leq 15.8938$	Zone 2, cooling mode. Zone 3, cooling mode. Zone 4, cooling mode. Zone 1, heating mode. Zone 2, heating mode. Zone 3, heating mode. Zone 4, heating mode. Zone 5, heating mode. Cooling mode
			$0 \leq \Delta P_{nwk} \leq 15.8938$	Heating mode.
GHE	3.53	$T_{g,init} = 16$		
	3.54	$\alpha_0 = 2.2727$ $\alpha_0 = 0.2494$ $\alpha_0 = 0.49$ $\alpha_0 = -0.2494$		
WAHX	3.43	$Cf = 1.000$	$3 \leq T_a^{in} \leq 35$	Cooling and heating modes.
		$A = 87.5083$ $U = 0.4000$	$2 \leq T_w^{in} \leq 30$	
	3.44 3.45 3.46	$\alpha_0 = 5.7500 \times 10^{-2}$	$7 \leq \dot{m}_w \leq 28$ $178500 \leq \dot{m}_a \leq 179000$	
BIPV	3.49	$loss_{mm} = 0.1$ $loss_{OHM} = 0.17$ $Ktemp = 0.5$ $120 \leq PV_{sf} \leq 200$ $0.1430 \leq \eta_{PV} \leq 0.1590$ $0.9460 \leq \eta_{INV} \leq 0.9520$	$0 \leq Gi_\omega \leq 1800$ $2 \leq T_{PV} \leq 40$	Ranging from 10 to 90°C
ESS	3.50	$0 \leq \eta_{ESS} \leq 0.9600$		

TABLE 4.4: Parameters and variable values for the component-level models used in the case study.

$$\begin{aligned}
\text{minimize } C_{\dot{E}} = & \sum_{t=1}^m E_{ele_rate,t} \times \left[\dot{E}_{WAHX,t} + \dot{E}_{dist,pump,t} + \sum_i^3 \dot{E}_{e,pump,t} + \right. \\
& \sum_i^3 \dot{E}_{c,pump,t} + \sum_{i=1}^3 \dot{E}_{hp,i,t} + \sum_{i=1}^{pwl} (1 - \eta_{ESS,i}) \\
& \left. + \dot{E}_{ESS,i,t}^{in} \right]
\end{aligned} \tag{4.2}$$

	Treatment
T_g, η_{ESS}	Discretized to a set of fixed values.
$\dot{m}_{nwk}, \dot{m}_w$	Fixed values - Evaporator and condenser pumps operate at fixed speeds.
T_c^{in}	Correspondingly discretized due to T_g
T_e^{in}	Fixed value, based on a conservative estimate of the highest possible return temperature which will not compromise on comfort temperatures.

TABLE 4.5: Treatment of temporary parameters in the selected component models.

Variables	Type	Description
T_e^{in}	Discretized	Return water temperature to the evaporator. Discretized if in heating mode.
T_c^{in}	Discretized	Return water temperature to the condenser. Discretized if in cooling mode.
$T_{e,i}^{out}$	Continuous	Heat pump evaporator setpoint temperature, cooling mode only.
$T_{c,i}^{out}$	Continuous	Heat pump condenser setpoint temperature, heating mode only.
$\dot{m}_{z,i}$	Continuous	Flowrate to each zone.
$\Delta T_{z,i}$	Continuous	Temperature difference of each zone.
$\Delta P_{z,i}$	Continuous	Pressure difference of each zone.
T_g	Discretized	Ground temperature.
η_{ESS}	Discretized	Battery efficiency.
$\dot{m}_a$	Continuous	Air flowrate for WAHX.
$\dot{E}_{ESS}$	Continuous	Battery charge/discharge.
$\dot{E}_{grid}$	Continuous	Grid electricity draw.
$Y_{hp}, Y_{WAHX}, \text{etc.}$	Binary	Binary variables to enable activation and deactivation of each component.
Parameters	Description	
$\dot{E}_{pv}$	Available solar energy.	
$E_{ele_rate,t}$	Hourly electricity unit cost.	
$\dot{m}_{c,i}$	Condenser flowrate.	
$\dot{m}_{e,i}$	Evaporator flowrate.	
T_{amb}	Ambient temperature.	
$T_{g,init}$	Initial ground temperature.	
T_{app}	Approach temperature for the WAHX.	
$\Delta T_{limit,z,i}$	Temperature difference limit for each zone.	
$\dot{Q}_{d,z,i,cm/hm}$	Cooling/heating demand.	

TABLE 4.6: Variables and parameters of the optimization problem.

Equations of the abstracted models discussed in *Section 3*, serve as constraints in problem formulation. The discretization of T_e^{in} or T_c^{in} and parameterization of $\dot{m}_c$ and $\dot{m}_e$ allows the electricity consumed by the heat pump to be expressed as:

$$\dot{E}_{hp,i} = f(T_{e,i}^{in}, T_{e,i}^{out}, T_{c,i}^{in}) \quad (4.3)$$

Since the flowrate of the evaporator and condenser pumps are constants, $\dot{E}_{e,pump,i}$ and $\dot{E}_{c,pump,i}$ will undertake only constant or null values depending on whether the optimizer chooses to have them activated.

Electricity consumed by the distribution pump is not only dependent on the total flowrate through the hydronic network by also the pressure difference - determined partially by the regulation of valves implicit to the pump and network model. The electricity consumed by the distribution pump is:

$$\dot{E}_{dist,pump} = f(\dot{m}_{z,1}, \dots, \dot{m}_{z,5}) \quad (4.4)$$

Constant $\dot{m}_e$ and $\dot{m}_c$ values result in $\dot{m}_w$ also being a constant. Additionally fixing the approach temperature (T_{app}), allows the following expression:

$$\dot{E}_{WAHX} = f(\dot{m}_a) \quad (4.5)$$

The final term $(1 - \eta_{ESS,i})\dot{E}_{ESS,i,t}^{in}$, is included to account for losses incurred during the charging process of the battery. Additional model-specific constraints listed in [Section 4.6](#) are not discussed here.

4.5.3 Modeling error

75% and 25% of the processed data are used for training and evaluating the models respectively ([Figures 4.7 and 4.8](#)). The MAEs for the models representing the heat pump and distribution pump are 4.79% and 11.27% respectively. Similar values were posted for the evaporator and condenser pumps. The chief causes of inaccuracies were found to be noise in the sensor readings and data aggregation over the hourly time-horizon. Despite so, the fidelity of the models' performance, in reality, is preserved.

FIGURE 4.7: Heat pump error plots.

FIGURE 4.8: Distribution pump error plots.

4.5.4 Simulation of base cases

The base cases defined in *Section 4.3.1* are also simulated using the models that were chosen. This serves as a fair benchmark for the evaluation of the optimal results obtained.

4.6 Results and discussion

For each of the four case-study scenarios, the comparison of the results of the base and optimization cases for each of the 12 days selected to represent the year is first shown. After this, the findings are explained by using results from a selected representative day as an example.

4.6.1 Case-study scenario 1: Energy optimization of the hydronic network.

This case study focuses on the operation of distribution pumps in the hydronic network. *Figure 4.9* illustrates the electricity consumption of the distribution pumps operating under three different control strategies - constant speed, variable speed, and optimized pressure setpoint. *Table 4.7* documents the comparison of electricity saving across the three operating strategies.

The switch from constant speed pumps to variable speed pumps could potentially result in electricity savings of about 19.8%. The bulk of these savings is attributed to the ability for the speed of the pump to be automatically adjusted in tandem with the flowrate demands. However, variable speed pumps are typically operated at a pre-determined pressure setpoint, which is determined through an estimate of a pressure differential which can deliver the required flowrate for the highest demand of a given period. By adapting the pressure setpoint in response to the hourly flowrate requirement, additional electricity savings could of 63.16 % result.

Using a typical day in July as an example (*Figure 4.10*), the pressure setpoint of the variable speed pump is relatively too high for large periods of the day. While it is understandable that the setpoint is determined by the peak demand of a given

period, considerable savings will result if it could be adapted according to demand, especially during the wee hours' of the day.

FIGURE 4.9: Approximate distribution pump electricity consumption under three operating strategies.

bc1 vs bc2	bc1 vs opt1	bc2 vs opt1
19.80%	70.79%	63.16%

TABLE 4.7: Comparison of average electricity savings in the distribution pumps across different operating strategies.

4.6.2 Case-study scenario 2: Operation cost optimization.

Batteries in our GCHP system exist for storing excess solar energy which could not be fully utilized. However, more could be done with these batteries - storing electricity from the grid when the price is favorable. The cost-saving potential exists in such a measure. The optimizer has the option of storing electricity from the grid when the price to optimize operating costs. *Figure 4.11* illustrates the potential monthly cost savings between the two battery operating strategies - storing only when there is excess solar energy and optimized battery storage which also permits storing electricity from the grid. For a given year, approximately 12.73% of the current operating cost could be reduced.

FIGURE 4.10: Comparison distribution pump pressure setting between *bc2* and *opt3* for a typical day in July.

The difference in battery operation is clearly illustrated in *Figure 4.12*. Electricity was drawn from the grid to be stored in the battery at 0300 and 0700 hours, just before the spike in electricity pricing occurred. This is the primary reason for the cost savings. Other differences in battery operation are inconsequential as they occur when the electricity price remained constant. Storage of electricity from the grid is a difficult decision as it involves determining the trade-off among the losses due to battery charging inefficiencies, cost savings, and future electricity demand, thus, best left to an optimizer.

4.6.3 Case-study scenario 3: Energy optimization including WAHX.

Holistic optimization enabled the identification of key bottlenecks in the GCHP system. It is difficult to significantly improve the energy performance of the GCHP system as the heat pumps are consistently subjected to unfavorable ground temperatures for prolonged periods. This implies a possible under-sizing of the GHE for the system. The only possible way to improve operating temperatures of the heat

FIGURE 4.11: Comparison of average operating cost between two battery operating strategies.

FIGURE 4.12: Difference in battery operation across a 24 hour period in June.

pumps is to provide an alternative to the GHE, hence we introduce a theoretical WAHX to the system.

Figure 4.13 compares the average monthly electricity savings when the operations of the hybrid GCHP system is holistically optimized (*opt3*) as compared to the current state (*bc3*). Electricity savings across the year averaged at 12.71%. The greatest savings occurred during the months where the thermal (cooling) demand was the highest.

The daily operation of a typical day in July is used as an example to unveil the reasons behind the electricity savings (*Figure 4.14*). Without an alternative for the GHE, recovery of the ground temperatures for *bc3* becomes impossible and begins to rise until it hits a plateau. $33\text{ }^{\circ}\text{C}$ is a relatively high condensing temperature for the heat pumps considering that the ambient air temperature is lower. Under the operating strategy provided by *opt3*, the WAHX is activated whenever the ground temperature starts to rise. By dissipating the condenser heat into the ambient air instead of the ground, it enabled the ground temperature to gradually recover to its initial state.

The WAHX is typically an inferior alternative to the GHE for the two ensuing reasons - additional electrical consumption from fans and less favorable condensing temperatures as they are dependent on ambient air temperatures. This is most evident during 0700, 1400 and 1700 hours where the optimal operation consumed more electricity than current practice. It was a necessary sacrifice for the benefit of the enhanced overall performance of the day. The corresponding system *COP* is plotted in *Figure 4.15*. The limits of the hybrid GCHP system are apparent towards the final hours of the day, wherein spite of superior condensing temperatures, the *COP* of the system only posted marginal improvements due to the heat pumps being operated at extremely low part-load conditions.

4.6.4 Case-study scenario 4: Operation cost optimization including WAHX.

Adding a WAHX to the GCHP system will require monetary investment, and thus should be justified with the savings from operation cost. In this case-study scenario, a comparison between a holistically optimized hybrid GCHP system for

FIGURE 4.13: Comparison of average monthly electricity consumption between current operating practices and optimization with WAHX.

FIGURE 4.14: Plot of electrical consumption and ground temperatures between $bc3$ and $opt3$ for a typical day in July.

FIGURE 4.15: Comparison of COP and ground temperatures between $bc3$ and $opt3$ for a typical day in July.

two objectives - electricity consumption and operating cost, against the current state. *Figure 4.16* details the monthly average operating cost under three different cases $bc3$, $opt3$ and $opt4$. The average cost savings across the three operating cases are shown in *Table 4.8*. While there exist considerable cost savings when the GCHP system was optimized for electricity consumption, an additional 28.17% could be realized, when instead optimized for the minimization of operating costs.

The explanation for this additional savings becomes evident when we delve deeply into the optimized results for any given day. A typical day in July is used as an example for discussion purposes. The difference in battery operation could probably explain the difference in operating costs between $opt3$ and $opt4$. As shown in *Figure 4.17*, the excess electricity from solar photovoltaics is never stored in the batteries in $opt3$, when the total electricity consumption is minimized.

Storage of electrical energy in batteries incur losses during the charging process, thus abstained from in $opt3$. However, with operating cost as the objective function, it then became necessary to store not only the excess electricity from solar photovoltaics but also electricity from the grid when the price is considerably lower - as it can be used to supplement electrical demands when the price increases. This

additional electricity stored, influenced the operation of the hybrid GCHP system in terms of electrical consumption - the inconsequential poorer efficiencies during periods of excess electricity 0400 - 0800 hours, and the considerably better performance during periods where electricity price is high (*Figure 4.18 and 4.19*). There even exist scenarios where the WAHX was activated just before the sharp increase in electricity price as shown in *Figure 4.18* at 1100 hours. This was likely done to improve the *COP* of the heat pumps when the electricity price is higher. Accounting for the trade-off between components of a tightly-coupled system is complex, and non-intuitive, thereby highlighting the benefit of performing optimization.

From a survey conducted, a typical WAHX suitable for the GCHP system is priced at approximately 25 000 €. Optimization results indicate potential cost savings of about 5600 € when *opt4* is compared to *bc3*. This indicates roughly that the payback period is likely to occur under five years. Finally, a plot of the break down of electricity consumption across all the seven cases in the case study is shown in *Figure 4.20*. The individual components started operating differently as more components are added to the optimization problem, demonstrating the benefit of performing optimization holistically and giving consideration to the tight-coupling between them. Finally, it is important to note that the optimization of operating cost does not correspondingly lead to the best energy performance, as evidenced by *opt3* and *opt4*.

bc3 vs opt3	bc3 vs opt4	opt3 vs opt4
11.13%	35.79%	28.17%

TABLE 4.8: Comparison of average cost savings across different operating strategies of the GCHP system.

4.7 Conclusion

Abstraction techniques on judiciously selected models can be leveraged to increase compatibility with the commonly deployed MILP format to increase the solvability of holistic system optimization problems. This effect, coupled with the vast benefit of holistic optimization of urban energy systems was highlighted in this chapter through a case study based on an existing GCHP system.

For enhancing the appreciation of holistic optimization, four case-study scenarios were designed to progressively optimize the building-level GCHP system. Through

FIGURE 4.16: Comparison of monthly average operating cost amongst $bc3$, $opt3$ and $opt4$.

FIGURE 4.17: Comparison of battery operation between $opt3$ and $opt4$ for a typical day in July.

FIGURE 4.18: Comparison of operating strategies among *bc3*, *opt3* and *opt4* for a typical day in July.

FIGURE 4.19: Comparison of system *COP* between *opt3* and *opt4*.

the analysis of the results, two key areas for electricity savings were identified - operation of the hydronic network and the improvement of ground temperatures.

FIGURE 4.20: Plot of electricity annual electricity consumption across all seven cases.

The latter was addressed through the hybridization of the GCHP system with a WAHX. Optimized results indicate potential electricity and cost savings of up to 12.7% and 35% respectively. With that, return on investment of the water-to-air heat exchanger is expected to be under five years. Such levels of savings would not have been possible without consideration of the tight-coupling between the components and holistic optimization.

Currently, the scalability of this methodology is limited as it is dependent on case-study specific information to restrict the problem formulation within the realms of MILP. As seen in *Table 4.5* and *4.6*, there are glaring limitations to the linearization techniques, especially when the relationships amongst the decision variables exceed the second-order. Hence, important decision variables such as T_g and $T_{c,e}^{in}$ have to be discretized to maintain compatibility with the mathematical program. Doing so not only increases the size of the problem but also limits solution space by restricting these decision variables to a set of artificially fixed values. As the number of linear-steps increases, the mathematical program gets increasingly inconvenient to formulate. Hence, a solution is needed to address this issue proper exploration of the solution space.

The next chapter address this shortcoming through the introduction of a hierarchical optimization framework.

Chapter 5

Hierarchical framework for holistic optimization

5.1 Overview

Formulation of an optimization problem that adequately captures the tight-coupling amongst components of urban energy systems and in terms of its tuneable variables often results in a MINLP which is large and difficult to solve. In the previous chapter, while abstraction techniques alone, permitted the GCHP system to be holistically optimized, it depended heavily on case-study specific characteristics, and discretionary discretization of the selected models to confine the problem within the realms of MILP. The former limits the possible use-cases and the latter is cumbersome to formulate for mathematical programming purposes; hence, it is unlikely to be scalable for use with generic urban energy systems.

A hierarchical framework of holistic optimization of the operations of urban energy systems is introduced to manage the MINLP. This framework introduces the GA in addition to the MILP which is formulated using abstracted component-level models. The introduction of the GA enables the decision variables which cannot be linearized to be optimized as well. With the MILP solver reducing the search space of the GA, the likelihood of achieving global optimality is greatly enhanced. This effect becomes evident when a performance comparison was made between

²The work in this chapter has been published in [170]

this framework and the sole use of metaheuristics (GA) for operation optimization in a case study based on an existing district-level energy system (DCS) in Europe.

This chapter begins by briefly highlighting the limitations in the existing literature pertaining to the operation optimization of DCS. After this, the hierarchical optimization framework is introduced and applied to the DCS. *Section 5.6* matches the performances of this framework against the sole use of the GA for the same problem, before providing a discussion of the which could have only been obtained through holistic optimization of the system. This methodology has been published in [170].

5.2 Introduction

The demand for space cooling accounts for a significant portion of energy demand. This statistic is even more valid in regions experiencing significant periods of tropical climates [171]. The percentage of energy used for space cooling in Mumbai (40%) is doubled that of London (20%) [172, 173]. DCS represents one such example of a potentially more efficient means of fulfilling this demand [13]. Thus, DCSs are rapidly becoming a standard feature in new city developments [174, 175]. The performance in reality, however, is uncertain as operating and design conditions differ[5]. The tendency to exercise caution in design often leads to the oversizing of DCS; this results in the underutilization of equipment which is especially detrimental to the overall energy efficiency of the system[176, 177].

Inefficiency is further compounded by control strategies that are either based on predefined setpoints or seek only to achieve optimal performance, local to components [6, 7]. Localized control disregards the cascading effect on the system which inhibits the ability of DCS to adapt well under less-than-ideal operating conditions. The focus of the current work is to introduce an optimization framework which thoroughly explores the solution space mapped by tuneable variables in a DCS, in search of improving energy efficiency holistically at the system-level.

5.2.1 District cooling system

A DCS is a centralized method of cold thermal energy production and distribution for space and process cooling. Chilled water is widely used as the medium for the transportation of thermal energy for cost-effectiveness [12]. The technical description of a typical DCS is comprised of four main components - the central station, distribution network, customers and heat rejection system. *Figure 5.1* illustrates the general components of a typical DCS serving four buildings. Cooling towers often serve as the primary equipment used for heat rejection. The active components of the DCS which consume electricity are the chillers, pumps and cooling towers. The rate at which electricity is consumed is dependent on the equipment loading, temperature, and flowrate setpoints.

FIGURE 5.1: Overview of the components of a typical DCS.

5.2.2 State of the art

The majority of the optimization work done on DCS and closely related district heating systems (DHS) are focused on presenting solutions to design-related issues [12, 93]. Such problems attempt to determine the optimal configurations of equipment type, primary resource, network layout, and customer configuration. They

employ methods and models which are too abstract for optimizing DCS operations - an example would be the assumption of constant efficiencies, regardless of equipment loading [21, 22]. Conversely, optimization of DCS operation is concerned with determining the most efficient equipment staging, flowrate and temperature settings which fulfills a given cooling demand [19, 20]. Thus, greater modeling detail of components is required.

Component-level optimization is commonplace where DCS operations are concerned. For a given cooling demand, these formulations attempt to determine the optimal operating plan for equipment [19] and the distribution network [20] separately. Detailed modeling of equipment and network hydraulics involved complex equations, which yields MINLP problem formulations making the use of meta-heuristics a popular choice [95, 178].

Several measures were employed to enhance the solvability of the above component-level optimization problems. Sakawa et al. [99] relaxed the cooling demand constraint by reflecting the failure to meet demand as a penalty in the objective function. With the use of appropriate equation-based models, the MINLP could be broken down into simpler quadratic programs (QP), under the assumption that the set of chillers could be aggregated as a single optimal unit [19]. If the distribution network is extensive, the energy expended for pumping could significantly affect the overall system performance. The relatively small working temperature range further compounds the impact for DCS [178]. To simplify the network optimization problem, Schweiger et al. [20] decomposed the MINLP problem into a mixed-integer quadratically-constrained program (MIQCP) and a smaller non-linear program (NLP). This approach reduced the non-convex search space while enabling models of higher detail and physical accuracy to be considered in the problem formulation.

There is no indication that the independent optimization of equipment and network will yield the optimal performance at the system-level. Thus, Jing et al. [95] modeled and optimized the operation of a small-scale district heating and cooling (DHC) system with the consideration of both equipment and network. The formulation enabled the power incurred by the pumps in the network to be reflected in the objective function. However, the direct application of the group search optimizer (GSO) algorithm, does little to ensure the quality of the final solution.

Work on building level optimization of chiller systems is also considered due to their relevance [100, 102]. They, however, tend to mainly focus on solving ‘optimal chiller loading’ (OCL) problems, with little regard for the details of the network, nor the setpoint temperature of chillers. Due to the differences in the scale of a DCS compared to the building level, the energy expended in the network has to be factored. The benefits of holistic system optimization were highlighted in a case study conducted on a building-level chiller plant, where an additional 6.5% of energy savings is possible on top of chiller-only optimization [167].

From the review, it is evident that there is a lack of studies that consider the holistic optimization of DCS operation, much less a systematic framework for this undertaking. Several studies on the closely related topic at the building level, consider fixed temperature setpoints of chillers, effectively misrepresenting the solution space. For a chiller-based system, the concurrent optimization of temperature setpoints and flowrate in response to a given cooling demand proved to be most effective in the minimization of electricity consumption [179]. DCS is also likely to benefit more profoundly from the consideration of temperature variables as it introduces flexibility into an inherently rigid system. Hence, the novelty of the current work lies in the introduction of a framework which can simultaneously optimize all tuneable variables of a DCS for a given cooling load.

5.2.3 Objectives

The hierarchical optimization framework for the holistic optimization of DCS operation is developed for managing the MINLP. It decomposes the optimization problem into two levels - a master and a slave. The key features of the master and slave levels are the GA and MILP solver respectively. This approach functions by having the GA parameterize a subset of variables such that the remaining can be dealt with using the MILP. Given that MILP solvers generally both converge optimally and more quickly than GAs, model abstraction techniques are used to linearize the DCS model as much as possible. Doing so, also reduces the load on the GA, promoting resolution speeds and the likelihood of deriving solutions that are globally optimal.

For illustrative purposes, this framework is applied to a case study based on an existing DCS in Europe. Three scenarios, each with different cooling demand

and weather conditions, are defined to demonstrate and quantify the potential electricity savings through the application of the proposed framework. Results indicate electricity reduction of 31%, 27% and 3% across high, moderate and low cooling demand conditions respectively.

5.3 Optimization framework

Taking reference from the approach used by Fazlollahi et al. on district heating/energy systems [91–93], a hierarchical framework for the operations optimization of urban energy systems is proposed. The decomposition method used is the core of the framework. It is introduced to deal with nonlinearities in the optimization problem.

It is apparent from the issues on model abstraction, highlighted in *Chapter 3* that a method is required to deal with variables held at constants. MILP can only solve the problem partially (*Chapter 4*). As such, the decomposition approach is employed to couple the MILP formulation with a metaheuristic. The purpose of this metaheuristic is to handle variables that the MILP solver can not. It treats the MILP formulation as a larger ‘black-box’ to be optimized. This approach is also beneficial to metaheuristics - having the MILP formulation handle most of the variables reduced the search space, improving solution quality whilst reducing resolution time.

The workings of the hierarchical framework which deploys the GA and the MILP at the master and slave levels are best illustrated with an example. Consider the following scenario - there are ten decision variables to be optimized, and holding two of them constant will enable the remaining eight to be conveniently formulated as a MILP. This means that another measure has to be introduced to optimize these two decision variables. The hierarchical framework introduced in this chapter deploys the GA for optimizing these two decision variables. During every iteration of the GA, the values of the GA decision variables are passed on to the MILP, for which they are treated as constants. For the current values of the GA variables (MILP constants), the eight MILP decision variables are optimized. The objective function of the MILP will then be communicated back to the GA for fitness evaluation. This is done as many times until the convergence criterion is met.

Figure 5.2 illustrates the overview of the proposed optimization framework. The proposed framework improved on the optimization work found in the current literature by considering higher levels of modeling detail. These details (temperature, network operation, the granularity of time-periods, etc.) are critical in the determination of design/operation feasibility. Flexibility was another feature of the framework. New models (equipment, natural resources, etc.) can be easily added without major modifications.

FIGURE 5.2: Overview of the optimization framework.

5.3.1 Pre-optimization

The nature of the problem and available data influences the choice of optimization approach and algorithms. This phase accomplishes the preparatory work for the formulation of the optimization problem. The following list details the key steps involved in a general optimization problem related to urban energy systems.

1. Objective function definition

Minimization of electricity consumption, emissions and cost represent some of the most common choices in literature. Some may be more relevant in design

rather than operation problems. The eventual choice will influence the data and models required to reflect it. At times, more than one objective function could be established, and multi-objective optimization could be performed.

2. Data management

The choice of objective function determined the requires data. Two types of data are usually required - ‘constraint’, ‘operation’ data. ‘Constraint’ data reflects the physical/geographical constraints onto the optimization problem. Minimum and maximum equipment capacities, contractual agreements, infeasible network routes, weather conditions, cooling demand, etc. are examples of these data types. ‘Operation’ data refer to those required to train a selected model. A record of temperature, flowrate, and electricity consumption variation over a period of time for chillers is one such example. The raw data has to undergo cleansing and structuring into usable formats for further use.

3. Model selection, training and algorithm selection

The models are selected and trained with the processed data. Based on the nature of the selected models, the optimization approach is determined. There is a preference for global optimality solvers. The extent of its applicability, however, depends on the selection of the available models. After the algorithm is selected, the model abstraction process will entail.

4. Simulation model

The simulation model comprises of abstracted models. Aside from quick testing of ‘what-if’ scenarios, the model also functions by ‘seeding’ metaheuristics with a starting feasible solution. Doing so ensures that the generated optimal result will always be equal to or better than a certain pre-defined level. For the optimization of operations, the ‘seeded’ value could be derived from the current working conditions. The simulation will also serve as a benchmark for comparison against the ‘optimal’ results generated.

5.3.2 Master level

The GA is used at this level owing to its popularity for solving such problems. This algorithm was utilized to handle non-linear variables, which were to be treated as

constants for the feasibility of MILP formulations. T_e^{in}, T_c^{in} etc. are examples of variables which can be handled by the GA (*Figure 3.3*) such that MILP can handle the remaining ones.

The GA is a population-based global search algorithm. The following list details the steps involved for a generic implementation [180].

1. **Parameter definition**

Key parameters (population size, generations etc.) and the bounds of the variables are defined.

2. **Initialization**

An initial population of p sets of variables (agents) is randomly selected and their fitness (objective) function evaluated.

3. **Selection**

Selection of $n \leq p$ agents are selected for offspring production. Selection is normally based on the fitness function. Probabilistic measures are usually introduced to reduce the likelihood of elitist selection.

4. **Crossover**

The selected n agents need to mix to produce $(p - n)$ ‘offspring’ agents. The extent of mixing is randomly determined. This is done on the assumption that better parents tend to have better offsprings (fitness function).

5. **Mutation**

A low percentage (k) of agents within the population is to be subjected to mutation. This means randomly changing the variable values within the agent. Doing so ‘maintains’ the ‘genetic’ diversity of the selected population. This step discourages convergence to local optima.

6. **Fitness evaluation / Termination**

The fitness function of the new population is evaluated again and steps 3 to 5 will be repeated until a stopping criterion is met. Termination happens after m generations or when the change in optimal value generated is considered to be small.

FIGURE 5.3: Overview of the generic genetic algorithm.

Parameters p , n , m , and k have to be properly selected for the algorithm to function well. *Figure 5.3* summarizes the generic genetic algorithm.

5.3.2.1 Current implementation

The GA can be implemented in several ways. The chosen implementation was targeted at improving resolution speeds. Slight modifications are made to the implementation shown in *Figure 5.3*.

Binary implementation

The implemented GA is coded in binary to facilitate the crossover and mutation process. The reduction of variables to binary enabled a higher level of control over the granularity of change during mixing processes while reducing the search space simultaneously. This implementation is motivated by the original purpose of the GA - to solve combinatorial problems effectively. The following highlights the key changes that were made for this implementation.

1. Parameter definition

Besides the definition of the lower and upper bounds of the variables to be optimized, the precision (decimal points) of the variable and the ‘variable

type' is required as an input. Precision is required to determine the number of binary bits required, while 'variable type' determines how the variable is handled. There are three predefined 'variable types' - binary, continuous and discrete.

There is no need for binary variables to be treated. For continuous variables, the defined precision effectively determined the number of possible values the variable can take. Consider the variable x such that $0 \leq x \leq 10$ with the precision of 1 decimal place. This effectively means that there are only 101 (0.0 to 10.0) possible values of x . Converting 101 to binary requires 7 bits. Discrete variables are handled in a similar way, where the number of discrete values determines the number of bits required. Since the conversion of decimal to binary is not exact (2^n), some variable values have a slightly higher probability of representation, however, the impact is diminished with longer binary strings.

2. Crossover

Consider the optimization of a three-variable problem - x_1, x_2 and x_3 represented by 3, 4 and 5 bits respectively. Every bit is treated equally, thus the crossover point can occur anywhere between the 1st to 12th bit. As a result, the crossover function can have greater control over offspring generation which is otherwise missing when the variables are treated as though they are continuous (Figure 5.4).

FIGURE 5.4: Crossover sites of continuous and binary implementation.

3. Mutation

The bit length used for each variable is recorded. The probability of a bit being subjected to mutation depends on two factors - the number of variables and its position within the binary string. Using the binary implementation

of the three-variable problem illustrated in *Figure 5.4* as an example, the probability of a mutation occurring within the first 3 bits is the same as the next 4 bits and the last 5 bits. This is implemented so that those with shorter bit lengths are not overshadowed. Within each variable, a linearly decreasing probability is implemented. Front bits have a higher chance of selection as they made greater changes to the value of the variable. This ensures the preservation of diversity.

Selection

Tournament selection is used as it is proven to perform relatively well in terms of resolution speed and solution quality [181]. Tournament selection involves selecting the best performing agent(s) from a randomly selected subset (size $j \leq p$) of the original population. This process has to be repeated until the required number of agents are met (size of crossover pool). Random selection of agents from the subset of size j reduces the risk of premature convergence.

Parallelization

GAs are ‘embarrassingly’ parallel programs. Parallelization can be implemented in many ways and should be taken advantage of especially with today’s computers’ ability to handle multiple concurrent processes. Cantú-Paz reviewed several methods of parallel GA implementations [182]. The global single-population master-slave parallel implementation is selected due to its ease of implementation. Having a single population eliminated the need for the development of communication ‘pipes’ between multiple populations. Thus, better-performing agents are more likely to contribute to offspring production. Such an implementation only involves the parallel evaluation of fitness values. That is very beneficial for the optimization framework as the evaluation of fitness values (solving MILP problems) is the most time-consuming part.

5.3.3 Model abstraction

Inputs from the master level are required for model abstraction to take place. Details of model abstraction techniques are discussed in *Chapter 3*. The focus of this section is to describe the method used for generating a MILP formulation from general bilinear equations. Three building blocks are defined to facilitate the MILP formulation - unit, layer, and constraint. Variables from the master level are treated as parameters in this stage.

5.3.3.1 Unit definition

The unit is modeled to represent a piece of equipment of the DCS (chiller etc.). It comprises up to 2 continuous variables (up to bilinear), some of which contribute to the objective function value. This means that bilinear relationships between the chosen variables are the complexity limit that this unit definition is capable of handling; any higher-order relationships will make the MILP formulation unnecessarily cumbersome, as shown in (*Chapter 4*). Where higher-order relationships are concerned, some variables should be optimized using the GA, making them constants at the slave level, thereby ensuring that the remaining variables fulfill the bilinear complexity limit.

The 2 selected variables are constrained by equations describing its capacity, and relationship with other units (streams). *Table 5.1* summarizes the unit definition.

The bilinear equations in *Table 5.1* are linearized using the RLT [142].

5.3.3.2 Layer definition

Layers are introduced to ‘connect’ the ‘streams’ flowing in and out of units. For DCS specifically, three stream-types are defined - fluid, temperature, and pressure flows. Ideally, equality constraints in the form of $st_{unit,1}^{out} = st_{unit,2}^{in}$ should be used to respect continuity equations. However such constraints resulted in difficulty for the GA to find feasible solutions.

To rectify the issue, inequalities are used instead. If the inequalities are used correctly, the optimal solution will never violate continuity equations. This is so

Input variables	Description
x_1	First variable.
x_2	Second variable.
Contribution to objective function	
$y = \alpha_0 x_1 + \alpha_1 x_2 + \alpha_2 x_1 x_2 + \alpha_3$	y represents the contribution to the objective function (electricity etc.). The objective function is the summation of contribution from all units.
Capacity constraints	
$F^{min}Y \leq \beta_0 x_1 + \beta_1 x_2 + \beta_2 x_1 x_2 + \beta_3 \leq F^{max}Y$ $F_{x_1}^{min}Y_{x_1} \leq x_1 \leq F_{x_1}^{max}Y_{x_1}$ $F_{x_2}^{min}Y_{x_2} \leq x_2 \leq F_{x_2}^{max}Y_{x_2}$ $Y_{x_1} + Y_{x_2} - 2Y = 0$	$F^{min/max}$ represents the limits on the unit/-variable. Using a chiller as an example, the limits can be used to represent its cooling capacity, flowrate, etc. Binary variables (Y) are introduced to turn the unit on and off.
Streams	
$st_i = \gamma_{0,i}x_1 + \gamma_{1,i}x_2 + \gamma_{2,i}x_1x_2 + \gamma_{3,i}$	Streams represent inflow and outflows of material (fluid, energy, temperature, etc.). These streams are used to interact with other units. A positive value of sr represents an inflow and vice-versa. There can be as many streams ($n = \sum i$) defined as required.

TABLE 5.1: A general unit description

as violating the equations will result in a sub-optimal solution.

There are occasions where the variables in the GA result in a feasible MILP formulation that violate continuity laws. A penalty function is imposed to reflect the extent of violation to the objective function of the GA. This penalty function is selected to be smaller than the penalty of infeasibility and acts as a guide for the GA to eventually converge to a feasible solution.

Table 5.2 describes the three layer types defined in the hierarchical framework.

5.3.3.3 Constraint definition

This feature is added to accommodate the need for additional constraints onto the problem formulation. Constraints can be of any form. The two commonly used ones are loosely termed as ‘unit-use’ and ‘stream-limit’ constraints.

Piecewise linearization breaks up a single model into several sub-models. That results in the need for multiple ‘units’ (Section 5.3.3.1) to be defined. However,

Layer type	Example equation	Description
Temperature	$\dot{m}_1^{out}T_1^{out} + \dots + \dot{m}_n^{out}T_n^{out} \leq \dot{m}_1^{in}T_1^{in} + \dots + \dot{m}_m^{in}T_m^{in}$	For DCS, the lower the supply temperature from the cooling source (chillers, etc.), the greater the electricity expended. As such, any optimal solution will try to raise the outlet temperatures as much as possible.
Fluid flowrate	$\dot{m}_1^{out} + \dots + \dot{m}_n^{out} \geq \dot{m}_1^{in} + \dots + \dot{m}_m^{in}$	Should greater fluid flow be supplied than required, more electricity will be expended by pumps and chillers leading to sub-optimal solutions.
Pressure	$\Delta P_1^{out} + \dots + \Delta P_n^{out} \geq \Delta P_1^{in} + \dots + \Delta P_m^{in}$	It is sub-optimal for a pump to supply greater pressure than required.

TABLE 5.2: Layers description

only one sub-model can be activated at any given point, thus the ‘unit-use’ constraint is required. The constraint is placed on the Y variable of the defined units (Table 5.1) such that $\sum_{i=1}^n Y_{unit,i} = 1$ where n represents the number of linear pieces.

‘Stream-limit’ constraints place a limit on the in and outflows of ‘units’. For instance, should the temperature of chilled water supply to a substation be required to be under T , this constraint can be used to achieve that.

5.3.4 Slave level

The MILP sub-problem is to be solved at this level. The objective of the MILP is to solve for the optimal values of the remaining variables, given the current values of the GA variables which are treated as constants at this level. This means that there are likely to be different MILP solutions for different values of GA variables.

The general format of a typical DCS sub-problem involving the minimization of total electricity consumption comprising of electric chillers, pumps, and cooling towers should look as follows,

minimize

$$\dot{E} = \sum_{i=1}^{n_{ch}} \dot{E}_{ch} + \sum_{j=1}^{n_{pump}} \dot{E}_{pump} + \sum_{k=1}^{n_{ct}} \dot{E}_{ct}$$

subject to

Capacity constraints (*Table 5.1*)

Layer constraints (*Table 5.2*)

Additional constraints (*Section 5.3.3.3*)

the output of the slave will be the optimal solution to the sub-problem based on variables selected at the master level. Due to the use of the RLT, the corresponding variable values (us and vs , etc.) of the optimal solution may not be in their original form and will need to be converted for readability in the next step.

5.3.5 Post processing

This section is included to process the results of the slave level. It is responsible for converting the optimal values of variables (us and vs etc.) back to their original forms (T , $\dot{m}$ etc.) for the sake of readability. It is also responsible for communicating the levels of infeasibilities back to the final objective function value (master level, GA). Currently, infeasibilities in the slave get an objective function value of 5 orders of magnitude higher than feasible ones violating continuity laws (*Section 5.3.3.2*). The purely feasible solutions get reflected to the master level as they are.

The difference in objective function values is meant to guide the selection of variable values of algorithms at the master level.

5.3.6 Summary

Figure 5.5 summarizes the hierarchical optimization framework which is designed to solve mono-objective MINLP. The decomposition method employed split the workload to the master and slave levels such that convergence can occur within a reasonable time. On average, it takes approximately 4 to 5 seconds to solve a sub-problem at the slave level. The majority of the computational time is spent

on the preparation of data in the ‘model abstraction’ stage (*Figure 5.2*).

The modular design of the optimization framework can easily accommodate changes in algorithms, models, and solvers. For instance, slight modifications to the algorithms at the master and post-processing stage levels can be done to accommodate multi-objective optimizations.

FIGURE 5.5: Complete parallelized hierarchical optimization framework

5.4 Model selection and abstraction

Table 5.3 documents the list of abstract component-level models which are required for representing the DCS in this case study. All model variables which were held constant for the sake of linearization are optimized by the GA in the hierarchical optimization framework.

Model description	Section
Chiller	3.3.1
Evaporator pump-network	3.3.3.4
Condenser pump-network	3.3.3.4
Distribution pump-network	3.3.3.5
Cooling tower	3.3.2

TABLE 5.3: Component-level models required for the DCS case study.

5.5 Problem formulation

5.5.1 Description

The case study discussed in this section is based on a functioning DCS located in Europe. The expected performance of a DCS is usually entirely different from reality owing to the limited information available during the design phase. Various factors could have contributed to the degraded performance of DCS; the lack of cooling demand and less than ideal system design are two common reasons for this occurrence. Development at the site of the DCS was slower than projected due to economic reasons. Without sufficient demand, the DCS cannot operate as efficiently as intended. Therefore, the purpose of this case study is to identify possible changes in operating practices that could potentially improve energy efficiency. The hierarchical optimization framework is employed for the undertaking.

The DCS of interest is comprised of a single central station serving four customers of different load profiles (commercial, retail, office). The central station houses three water-cooled chillers - one small and two large ones, cooled by an array of 5 cooling towers (*Figure 5.6*). *Table 5.4* documents the size of the components considered in the DCS model.

Current operating practices, coupled with low demand, often results in the infamous ‘low ΔT ’ syndrome’, where the pumps operate at near maximum capacity while chillers operate inefficiently at low part-load conditions. The purpose of this study is to investigate the extent to which operating practices can be tuned to improve energy usage. This is not a trivial task as it involves the adjustment of many dependent variables with unclear implications, resulting in the need for optimization to be done.

FIGURE 5.6: Schematic of DCS in case study.

The objective is to optimize the operation of DCS at the hourly level using the framework discussed in *Section 5.3*. Models discussed in *Chapter 3* are used to detail the DCS to the component level before the application of the optimization strategy. Demand conditions for three representative days with low, medium and high cooling demands were selected to illustrate the benefits of performing optimization on the system.

The input conditions such as the cooling demand profile and the ambient conditions are shown in *Figures 5.7 and 5.8* respectively. The exact data used can be found

Description	Nominal capacity	Quantity	Remarks
Chillers	2000(kWh)	1	Variable speed drive compressor, nominal cooling rate.
	7330(kWh)	2	Dual compressor, variable speed, nominal cooling rate.
Evaporator pumps	218.3903(m^3/h), 15(mmH_2O), 7.5(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	820.4531(m^3/h), 23(mmH_2O), 45(kWh)	2	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
Condenser pumps	561.0120(m^3/h), 30(mmH_2O), 45(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	1829.4721(m^3/h), 50(mmH_2O), 160(kWh)	2	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
Distribution pumps	632.3090(m^3/h), 40(mmH_2O), 45(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	778.9949(m^3/h), 50(mmH_2O), 75(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	1128.8211(m^3/h), 40(mmH_2O), 90(kWh)	2	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	1365.0266(m^3/h), 55(mmH_2O), 132(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	1699.6877(m^3/h), 65(mmH_2O), 250(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
	2195.7156(m^3/h), 75(mmH_2O), 450(kWh)	1	Variable speed drive, maximum flow and pressure, nominal electricity consumption.
Cooling towers	3542.4720 5667.9080(kWh), 22(kWh)	– 5	Nominal heat dissipation range, and fan electricity consumption at $T_{ct}^{in} = 35(^{\circ}C)$, $T_{ct}^{out} = 30(^{\circ}C)$, $T_{wb} = 26(^{\circ}C)$ and $\dot{m}_{ct}^{in} = 610(m^3/h)$ respectively.

TABLE 5.4: Size of components considered in the DCS.

in the tabular form in *Appendix E*.

5.5.2 Implementation of optimization framework

Table 5.5 describes the variables and parameters involved at each time-period. *Table 5.6* documents the model coefficients and the bounds of the variables considered in the case study. The variables are separated into master and slave level

FIGURE 5.7: Customer demand profiles of the three chosen periods.

FIGURE 5.8: Ambient condition profiles of the three chosen periods.

variables. These variables are handled separately in different phases of the optimization framework. Optimization of electricity over a 24-hour period involved 684 variables. The problem was simplified using the assumption that every time-period, comprising a 1-hour duration, is independent. The overall ‘optimal’ value, therefore, is the summation of ‘optimal’ values of each time-period.

Master level variables	Description
$T_{ct,unit}^{out}$	temperature of fluid exiting the cooling tower array and entering the condenser side of chillers.
$\dot{m}_{ct,unit}^{in}$	total condenser network flowrate.
$T_{dist,nwk}^{out}$	temperature of return fluid from the distribution network entering the evaporator side of chillers.
$\dot{m}_{sys}$	total evaporator/distribution network flowrate.
Slave level variables	
$\% \dot{m}_{e,i}^{out}$	percentage of total flowrate through the i th chiller evaporator.
$T_{e,i}^{out}$	fluid temperature exiting i th chiller evaporator.
$T_{c,i}^{out}(K)$	fluid temperature exiting i th chiller condenser.
$\% \dot{m}_{c,i}^{in}$	percentage of total flowrate through the i th chiller condenser.
$\% \dot{m}_{cp}$	percentage of total flowrate through the common pipe.
$\% \dot{m}_{ss,i}$	percentage of total flowrate through the i th customer's substation.
$\dot{m}_{a,ct,i}$	inducted air flowrate through each cooling tower.
$Pump_{sel}$	the choice/combination of distribution pump(s).
Parameters	
$\dot{Q}_{d,i}$	cooling demand of the i th customer substation.
T_{wb}	thermodynamic wet-bulb temperature.
$\Delta T_{ss,i}^{max}$	maximum temperature difference on the cold-side of the heat-exchanger at the substation.

TABLE 5.5: Parameters and variables associated with the case study.

5.5.2.1 Mathematical formulation

This section illustrates the mathematical formulation of the decomposition approach. The objective function is defined as the minimization of hourly electricity consumption of the DCS.

Master level

The overall objective function for each hour is defined as:

$$\text{minimize } \dot{E}_{DCS} = f(T_{ct,unit}^{out}, \dot{m}_{ct,unit}^{in}, T_{dist,nwk}^{out}, \dot{m}_{sys}) \quad (5.1)$$

Variables at the master level are treated as parameters at the slave level and used for the computation of various coefficients which ensures that the slave is a MILP. For each set of master level variables, the slave returns an optimal solution. The process is iterated until a convergence criterion is met.

Component	Equation	Coefficients	Variable bounds	Remarks
Chiller (small)	3.1 3.2 3.4	$\beta_0 = 0.1230$ $\beta_1 = 1044.7973$ $\beta_2 = 0.0204$ $\alpha_0 = 1.0986$	$0 \leq \dot{Q}_e \leq 2000$ $25 \leq T_c^{in} \leq 30$ $2 \leq T_e^{out} \leq 5$	Function of T_{wb}
Chiller (large)	3.1 3.2 3.4	$\beta_0 = 1.3504$ $\beta_1 = -134.8537$ $\beta_2 = 0.0043$ $\alpha_0 = 1.1034$	$0 \leq \dot{Q}_e \leq 7330$ $25 \leq T_c^{in} \leq 30$ $2 \leq T_e^{out} \leq 5$	Function of T_{wb}
Evaporator pump-network (small)	3.28 3.32	$\alpha = 2.4640 \times 10^{-4}$ $\beta_0 = 0.0229$ $\beta_1 = 0.2590$	$109.1951 \leq \dot{m}_{nwk} \leq 218.3903$ $0 \leq \Delta P_{nwk} \leq 15$	
Evaporator pump-network (large)	3.28 3.32	$\alpha = 3.0740 \times 10^{-4}$ $\beta_0 = 0.0322$ $\beta_1 = 0.7944$	$410.2266 \leq \dot{m}_{nwk} \leq 820.4532$ $0 \leq \Delta P_{nwk} \leq 23$	
Condenser pump-network (small)	3.28 3.32	$\alpha = 1.3370 \times 10^{-4}$ $\beta_0 = 0.0629$ $\beta_1 = 0.6721$	$448.8096 \leq \dot{m}_{nwk} \leq 561.0120$ $24 \leq \Delta P_{nwk} \leq 30$	
Condenser pump-network (large)	3.28 3.32	$\alpha = 1.7820 \times 10^{-5}$ $\beta_0 = 0.0533$ $\beta_1 = 1.6855$	$1463.5776 \leq \dot{m}_{nwk} \leq 1829.4721$ $40 \leq \Delta P_{nwk} \leq 50$	
Distribution pump-network	3.28 3.32	$\alpha = 8.3980 \times 10^{-4}$ $\alpha = 7.5640 \times 10^{-3}$ $\alpha = 6.5750 \times 10^{-4}$ $\alpha = 9.7590 \times 10^{-4}$ $\beta_0 = 0.0687$ $\beta_1 = 0.3693$ $\beta_2 = 0.4113$ $\beta_0 = 0.0950$ $\beta_1 = 0.4659$ $\beta_2 = 0.7291$ $\beta_0 = 0.0591$ $\beta_1 = 0.8909$ $\beta_2 = 3.4957$ $\beta_0 = 0.0883$ $\beta_1 = 0.6950$ $\beta_2 = 6.1848$ $\beta_0 = 0.0945$ $\beta_1 = 1.4109$ $\beta_2 = 12.0310$ $\beta_0 = 0.0874$ $\beta_1 = 2.7800$ $\beta_2 = 30.9186$	$0 \leq \dot{m}_{nwk} \leq 600$ $0 \leq \Delta P_{nwk} \leq 40$ $0 \leq \Delta P_{nwk} \leq 50$ $0 \leq \Delta P_{nwk} \leq 40$ $0 \leq \Delta P_{nwk} \leq 55$ $0 \leq \Delta P_{nwk} \leq 65$ $0 \leq \Delta P_{nwk} \leq 75$	Customer 1 Customer 2 Customer 3 Customer 4 Pump 1 Pump 2 Pump 3 & 4 Pump 5 Pump 6 Pump 7
Cooling tower	3.27	$-1.4131 \times 10^{-4} \leq \nu_0 \leq 4.2060 \times 10^{-4}$ $8.9810 \times 10^{-2} \leq \nu_1 \leq 0.6155$ $-1.4415 \times 10^{-6} \leq \nu_2 \leq 4.7652 \times 10^{-7}$ $-175.5735 \leq \nu_3 \leq -25.2736$	$18455.85 \leq \dot{m}_a^{in} \leq 369117$	Stepwise linearized throughout the operating range.

TABLE 5.6: Parameters and variable values for the component-level models used in the DCS case study.

Slave level

The objective function at the slave level is:

$$\text{minimize } \dot{E}_{slave} = \sum_{i=1}^{n=3} \dot{E}_{ch,i} + \sum_{i=1}^{n=3} \dot{E}_{e,nwk,pump,i} + \sum_{i=1}^{n=3} \dot{E}_{c,nwk,pump,i} + \sum_{i=1}^{n=7} \dot{E}_{dist,nwk,pump,i} + \sum_{i=1}^{n=5} \dot{E}_{ct,i} \quad (5.2)$$

With $T_{ct,unit}^{out}$, $\dot{m}_{ct,unit}^{in}$, $T_{dist,nwk}^{out}$ and $\dot{m}_{sys}$ treated as parameters, the electricity consumed by the chiller and the associated constraints are defined as:

$$\dot{E}_{ch,i} = f(\% \dot{m}_{e,i}^{out}, T_{e,i}^{out}, \% \dot{m}_{c,i}^{in}) \quad (5.3)$$

The flowrate percentages and temperatures are required for the calculation of electricity consumption of the chiller.

With the total network flowrates ($\dot{m}_{ct,unit}^{in}$ and $\dot{m}_{sys}$) fixed as parameters, the electricity consumed by the evaporator and condenser pumps could be expressed as follows.

$$\dot{E}_{e,nwk,pump,i} = f(\% \dot{m}_{e,i}^{out}) \quad (5.4)$$

$$\dot{E}_{c,nwk,pump,i} = f(\% \dot{m}_{c,i}^{in}) \quad (5.5)$$

The following equations are involved in the computation of the electricity consumed by the distribution pump given that $\dot{m}_{sys}$ is a parameter.

$$\sum_{i=1}^{n=7} \dot{E}_{dist,nwk,pump,i} = Y_{dist,nwk,pump,i} f(\% \dot{m}_{ss,1}, \dots, \% \dot{m}_{ss,4}) \quad (5.6)$$

$$\sum_{i=1}^{n=7} Y_{dist,nwk,pump,i} \leq 1 \quad (5.7)$$

Eq. 5.6 captures the impact of flowrate distribution in the parallel network on the pressure difference and hence the electricity consumed by the distribution pump.

Eq. 5.7 ensures that only one pump or pump combinations are selected for serving the distribution network. The selected pump is described by the variable P_{sel} .

Given $\mathbf{T}_{ct,unit}^{out}$, $\dot{\mathbf{m}}_{ct,unit}^{in}$ and T_{wb} as parameters, the electricity consumed by the cooling tower is,

$$\dot{E}_{ct,i} = f(\% \dot{m}_{c,1}^{in}, T_{c,1}^{out}, \dots, \% \dot{m}_{c,3}^{in}, T_{c,3}^{out}, \dot{m}_{a,ct,i}) \quad (5.8)$$

where $T_{c,i}^{out}$ is an output of the chiller model.

An heat-exchanger model was excluded due to the lack of control over the 'hot-side' of the substation as described in Section 3.3.3.5. The temperature difference at each substation is,

$$\Delta T_{ss,i} = \frac{\dot{Q}_{d,i}}{\dot{m}_{ss,i} \dot{\mathbf{m}}_{sys} C_{pw}} \quad (5.9)$$

$$\Delta T_{ss,i} \leq \Delta T_{ss,i}^{max} \quad (5.10)$$

Several additional constraints are needed to model the dependence between the equipment in the DCS. These are captured using the layer definition (Section 5.3.3.2). The flowrates in the DCS could be described by,

$$\sum_{i=1}^{n=3} \% \dot{m}_{e,i}^{out} \geq [\% \dot{m}_{cp} + \sum_{i=1}^{n=4} \% \dot{m}_{ss,i}] \geq 1 \quad (5.11)$$

$$\sum_{i=1}^{n=3} \% \dot{m}_{c,i}^{in} \geq 1 \quad (5.12)$$

The temperatures in the DCS could be described by:

$$\sum_{i=1}^{n=4} T_{e,nwk}^{out} + \Delta T_{ss,i} \leq \mathbf{T}_{dist,nwk}^{out} \quad (5.13)$$

$$\sum_{i=1}^{n=5} T_{c,nwk}^{out} + \Delta T_{ct,i} \leq \mathbf{T}_{ct,unit}^{out} \quad (5.14)$$

where $T_{e,nwk}^{out}$, $T_{c,nwk}^{out}$ and $\Delta T_{ct,i}$ could be calculated using the following equations,

$$T_{e,nwk}^{out} = f(\dot{m}_{e,1}^{out}, T_{e,1}^{out}, \dots, \dot{m}_{e,3}^{out}, T_{e,3}^{out}) \quad (5.15)$$

$$T_{c,nwk}^{out} = f(\dot{m}_{c,1}^{in}, T_{c,1}^{out}, \dots, \dot{m}_{c,3}^{in}, T_{c,3}^{out}) \quad (5.16)$$

$$\Delta T_{ct,i} = f(\dot{\mathbf{m}}_{ct,unit}^{in}, \dot{m}_{a,ct,i}, T_{c,nwk}^{out}) \quad (5.17)$$

The linearization process of the original models was described in *Chapter 3*. After the linearization process, the equations are structured in the form described in *Section 5.3.3*.

5.5.2.2 Modeling error

75% and 25% of the processed data were used for training and the evaluation of the models respectively (*Figure 5.9*). The MAE for the models representing the chiller, distribution pumps and cooling towers are 11.3%, 6.9%, and 1.8% respectively. The evaporator and condenser pumps report similar values to the distribution pumps. The aggregation of data over hourly time-horizon coupled with inaccuracies in the sensor readings was likely causes to the noise in the data. Nevertheless, the models can capture the performance of the equipment as evidenced by the plots.

5.5.2.3 Definition of a base-cases

Simulation of the current operating practices using the chosen models is used as a benchmark for the evaluation of the results derived from the optimization strategy. These operating practices were a mixture of commonly employed control strategies for chiller plants [6, 7]. Results of the simulation are also used for ‘seeding’ the GA to eliminate any chance of the optimal value being worse-off than the ‘base-case’.

Additionally, chiller-only optimization was also defined to highlight the benefits of performing holistic optimization on the DCS. For this scenario, each chiller is permitted to optimize independent variables of the unit, while respecting the

FIGURE 5.9: Error plots of the chosen models used in the case study.

constraints of other units. Table 5.7 lists the treatment of key variables in the both cases.

		‘Base-case’	‘Chiller optimization’	‘Holistically optimized’
Decision variables	ΔT_{app}	Fixed	Fixed	Variable
	$\dot{m}_{c,i}$	Fixed	Fixed	Variable
	$\dot{m}_{e,i}$	Fixed	Variable	Variable
	$T_{e,i}^{out}$	Fixed	Variable	Variable
	$\Delta T_{ss,i}$	Averaged from raw data.	Variable	Variable
	$Pump_{sel}$	Staged based on flowrates.		Variable
	$Y_{ch,i}$	Staged based on flowrates.	Variable	Variable

TABLE 5.7: Decision variable settings of the DCS in the three optimization cases defined.

All computations were done on a workstation with 16 GB of RAM, and an i7 4710HQ CPU clocked at 3.5 GHz on all cores. The cumulative time required for a single run of the model reduction to post-processing phases averages at 40 seconds.

Solving the slave sub-problem, however, only requires approximately 5 seconds. For the GA, a population size of 100 was defined and evaluated until there is no change in the objective function for 10 generations. For the MILP, the solver was set to terminate should the optimality gap between the lower and upper objective bound is below 10^{-4} .

5.6 Results and discussion

5.6.1 Comparison of approaches: GA-only and the optimization framework

The advantage of using the optimization framework over the direct application of the GA onto the case study is highlighted in *Figure 5.10*. Both methods were used to optimize the electricity consumption for a given demand for a single hour. The GA-only approach utilized non-linear models. Hyperparameter settings for the GAs used in both approaches are detailed in *Table 5.8*. The six trials were allowed to iterate for the same time duration.

Without the need to execute of MILP solvers, the GA-only approach could complete evaluating more generations than the optimization framework. However, the value of the final objective function from this approach left much to be desired - despite iterating through more generations; it did not deliver the same objective function value for each of the three trials. For the case of the optimization framework, the reduced number of variables that the GA had to deal with, likely allowed it to converge to a superior solution more quickly.

	GA only	Optimization framework
Number of GA variables	22	4
Population size	550	100
Tournament size	165	30
Crossover percentage	0.4	0.4
Mutation percentage	0.1	0.1

TABLE 5.8: GA hyperparameters for both approaches.

FIGURE 5.10: Performance comparison between the direct application of GA and the optimization framework.

5.6.2 Case study results

The cumulative electricity consumption of the DCS for the ‘base’, ‘chiller optimization’ and ‘holistically optimized’ cases are plotted in *Figure 5.11*. A decrease in electricity consumption of 31.93%, 27.38%, and 3.03% is observed across the three 24 hour periods representing high, medium and low cooling demand respectively between the first and third cases. *Table 5.9* details the breakdown of the decrease in electricity consumption by component.

For data confidentiality, all numbers are scaled by a common factor. The order of magnitude is still preserved.

Not all components experienced the same rate of decrease in electricity consumption despite the overall figures. This highlights the benefit of performing optimization holistically as compared to the chiller-only approach, as the results are not apparent. Overall, the savings in the operation of the pumps are the most significant contributors to the savings in electricity. Optimization of the chillers, independent of the pump operations neglected this opportunity for added electricity savings.

FIGURE 5.11: Result comparison of the three optimization cases over the three representative periods.

	'base' vs 'chiller optimization'	'base' vs 'holistically optimized'	'chiller optimization' vs 'holistically optimized'
High load	Percentage decrease in electricity consumed (%)		
Chillers	- 21.94	- 12.28	12.36
Pumps	- 8.24	- 58.95	- 55.26
Cooling towers	0.00	- 5.00	- 5.00
Overall	- 16.07	- 31.93	- 18.89
Mid load			
Chillers	- 12.45	- 1.36	12.66
Pumps	- 12.58	- 57.56	- 51.45
Cooling towers	0.00	0.00	0.00
Overall	- 12.51	- 27.38	- 17.00
Low load			
Chillers	- 4.81	0.06	5.12
Pumps	5.33	- 8.81	- 13.42
Cooling towers	0.00	0.00	0.00
Overall	- 1.28	- 3.03	- 1.77

TABLE 5.9: Percentage change in electricity consumption across the representative periods.

This effect is clearly illustrated when comparing the results of the chiller-only and the holistic approach. At the 'optimum' chillers were operated up to 12% less efficiently in the holistic as compared to the chiller-only optimization approach. The slight reduction in chiller efficiencies, enabled the pumps to be operated more

efficiently, thereby contributing to greater electricity savings for the entire system. The concurrent changes in chiller and network operation are the main reasons for this occurrence. The following discussions explain the reasons for the electricity savings from the perspective of the chiller and distribution network operation by comparing the results of holistic optimization against the ‘base’ case. The discussion omits the impact of the cooling towers as they were hardly in operation due to the relatively low ambient temperatures (*Figure 5.8*).

As there exists a minimum flowrate on the evaporator side of every chiller, more chillers in operation generally implied an increase in chilled water flowrate which loaded the pumps more heavily. The cumulative operating hours of the ‘holistically optimized’ cases are always lower than their corresponding ‘base’ cases (*Table 5.10*). This means that fewer chillers are activated to meet the cooling demand which results in a reduced load on the pumps.

		Working hours (<i>h</i>)			
		Chiller 1	Chiller 2	Chiller 3	Total
High-load	‘Base’- case	14	18	7	39
	‘Holistically optimized’	7	8	11	26
Mid-load	‘Base’- case	17	15	0	32
	‘Holistically optimized’	12	6	8	26
Low-load	‘Base’- case	18	9	0	27
	‘Holistically optimized’	16	7	2	25

TABLE 5.10: Working hours of chillers in DCS.

There could be several explanations for this occurrence. For illustration purposes, the chiller staging strategies and the flowrates in the distribution network for all three load scenarios are plotted in *Figures 5.12* and *5.13*. It can be seen that under the ‘holistically optimized’ operating strategy, there is a general preference for operating as few chillers as possible. For fewer activated chillers with lower flowrates to fulfill the same cooling demand, the chilled water supply temperatures ($T_{e,i}^{out}$) of chillers had to be lowered. These lowered temperatures increased the thermal energy content of the working fluid which enabled the cooling demand to be met. The impact of such an action is usually unclear; lower chilled water supply temperature increases compressor lift which decreases energy efficiency. Conversely, general improvements in loading conditions have the opposite effect. This effect is illustrated in the part-load performance plot of one of the chillers in the case study (*Figure 5.14*). Additional consideration of the impacts on pumps and networks further complicated the outcome.

Scenarios also exist whereby operating a larger chiller is more economical for the entire system. This can be seen from the period spanning from 0100hrs to 0700hrs across all three load scenarios (*Figure 5.12*). Operating a larger chiller means that the criteria for the minimum flowrate have to be raised (*Figure 5.13*). Raising the flowrate negatively impacted the ΔT of the distribution network. However, due to chiller 2 and 3 being dual-compressor systems, having a single compressor activated meant that it had the luxury of utilizing the entire heat-exchange surface area on both the condenser and evaporator sides. That results in a higher *COP* as compared to operating chiller 1 for the given load.

There are uncommon instances where (low-load, *Table 5.9*) where the ‘holistically optimized’ results suggest that chillers should operate less efficiently for the benefit of the overall system performance.

It is thus, worthwhile to investigate the operation of the distribution network since the pump operations at the ‘optimum’ are the largest contributors to the overall electricity savings. It has been established that the lower chilled water supply temperatures ($T_{e,i}^{out}$) reduces the overall flowrate and hence the load on the pumps. That, however, is only just one side of the equation. Comparison of *Figures 5.13* and *5.15* reveals a positive relationship between the flowrate ($\dot{m}_{dist,nwk}$) and the pressure difference ($\Delta P_{dist,nwk}$) in the distribution network. While that is generally true, the reduction of $\Delta P_{dist,nwk}$ could also be explained by another factor - valve regulation at the substation of customers’.

Most of the above explanations are focused on how lowering chilled water supply temperatures, reduces the overall flowrate in the distribution network and hence the electricity consumption of the pumps. *Figure 5.16* compares the temperature difference at the substation level ($\Delta T_{ss,i}$) between the ‘base’ and ‘holistically optimized’ cases. A reduction of distribution network flowrate should increase the value of $\Delta T_{ss,i}$ across the board, however, scenarios exist, at the ‘optimum’ where the value of $\Delta T_{ss,i}$ is lower than that of the ‘base’ case. Intuitively, this should not happen as only serves to degrade the return temperature to the chillers ($T_{dist,nwk}^{out}$), which will adversely impact the efficiency of chillers. The reason for this observation becomes clearer only when analyzing the results from the standpoint of network pressure difference. In a parallel network configuration with each branch independently controlled by a valve, the situation with the lowest flow impedance occurs when all valves are fully open. Partially closing a valve in any branch will

FIGURE 5.12: Comparison of chiller staging strategies between the ‘base’ and ‘holistically optimized’ cases.

(A) High-load

(B) Mid-load

(C) Low-load

FIGURE 5.13: Comparison of $\dot{m}_{dist_nwk}$ in the distribution network between the 'base' and 'holistically optimized' cases.

FIGURE 5.14: Impact of lowering chilled water temperatures at various points of the part-load curve.

serve to impede flow and subsequently increase the pressure difference of the entire network. Depending on the cooling demand scenario, it is hence, conceivable that some valves regulated such that more chilled water flows through a given substation than required. Doing so, despite compromising on $\Delta T_{dist,nwk}$ saves electricity by reducing $\Delta P_{dist,nwk}$. This effect is most commonly observed in the mid-load condition (*Figure 5.16b*).

The benefits of applying optimization to the DCS are highlighted in the case study. Optimization of DCS at the system level extended beyond the consideration of chillers alone. This was especially true in DCS where considerable energy is used in the distribution of chilled water, a key difference between district and building-level systems. There are even instances where a slight reduction of chiller efficiencies resulted in overall electricity savings at the system level. The reduction of chilled water supply temperatures to prevent another chiller from being activated is one such example. For a system with such tight-coupling between components, the best operating strategy is usually non-trivial.

There are limitations to the extent of improvement, however. At extremely low

loads, little can be done to improve the operation of the DCS. This is a design-related issue that has to be dealt with separately. The proposed methods of improving system performance can be used as short-term measures, as well as a guide for further improvements in design. For instance, it may not be ideal to supply chilled water colder than required for prolonged periods. Should the operation of DCS at part-load conditions be expected to prevail, perhaps the addition of a smaller chiller, storage or making changes to heat-exchangers at the substations could prove much more beneficial. Such conclusions can only be reached after conducting proper cost-benefit analyses.

5.7 Conclusion

In this chapter, a hierarchical framework for holistic optimization of the operations of urban energy systems has been introduced. This framework utilizes a combination of GA and MILP to solve MINLP problems in a bid to bridge the deficit between design and operating performance. It could also function as a tool that aids the decision-making process of operators' of such systems. Compared to the pure application of metaheuristics, the methodical decomposition of the complex MINLP problem in the proposed framework hugely benefited not only solution quality but also resolution time.

Through this framework and its subsequent application on a case study, the holistic-level is once again proven to be superior to component-level optimization. This is primarily derived from the modeling of interdependencies amongst the system-components at the appropriate fidelity. Finally, the limits of operation optimization also highlighted - operation optimization alone is no solution for an inherently inferior design ('low-load' condition).

The current state of the framework is plagued by one glaring issue, which is brought about by the GA - slow resolution speed. This is inevitable due to the population-based, iterative nature of the algorithm. The impact becomes compounded when the size of the optimization problem gets larger (i.e. energy storage, etc.). This framework as it is is not yet suitable for real-time deployment. To address these

(A) High-load

(B) Mid-load

(C) Low-load

FIGURE 5.15: Comparison of $\Delta P_{dist,nwk}$ between the 'base' and 'holistically optimized' cases.

(A) High-load

(B) Mid-load

(C) Low-load

FIGURE 5.16: Comparison of customer substation ΔT between the 'base' and 'holistically optimized' cases.

shortcomings, approximations (*Chapter 6*) are introduced together with machine-learning (*Chapter 7*) techniques to hasten the execution of the algorithm in real-time.

Chapter 6

Multi-period, multi-objective, holistic optimization

6.1 Overview

The inclusion of energy storage in urban energy systems burgeons the size of the optimization problem, making the already computationally intensive task intractable. Intractability occurs when there are just simply too many decision variables for the algorithms to handle or too many constraints to be conveniently formulated, resulting in excruciatingly long resolution times. The need to simultaneously solve for the optimal values across various time-periods for multiple objectives is the primary reason for this occurrence. The hierarchical framework introduced in the previous chapter does not perform satisfactorily for solving large scale problems, especially when there are many decision variables at the master-level. The GA's iterative nature and difficulty of expressing constraints at the master level are the two chief reasons for the inefficiency of *Chapter 5's* methodology.

To aid the solvability of the complex multi-period, multi-objective MINLP, the hierarchical framework is enhanced with a new feature - the sliding window technique. This new feature permits the limitation of the number of time-periods to be simultaneously solved, hence, benefitting the framework's resolution speed for energy-storage related optimization problems. This chapter begins with an introduction of the sliding-window technique and the limitations in the existing literature. Subsequently, the demonstration of the new version of the hierarchical

framework is done through its application on a case study in *Section 6.3*. Finally, the results of the case study are presented and discussed.

6.2 Introduction

For energy storage to be meaningfully incorporated into optimization problems, two additional features must be included - multi-period and multi-objective considerations. The primary existence of storage systems is to provision for energy to be stored in more favorable periods, which is then made available thereafter. This is mainly done for two reasons - to improve the energy performance or cost-effectiveness of the system. Improvements in energy performance are largely related to how the storages affect the operational efficiency of the system components. There usually exists a narrow bandwidth for peak performance in these components, failing to operate within, results in substantial penalties in efficiencies; energy storages aid the cause, by permitting these components to over/under produce energy irrespective of demand conditions so that efficiency is maintained. Hence, the inclusion of multi-period capabilities is paramount.

Another important reason for storing energy is to take advantage of the ratio of resource prices to energy production. Building-level systems for instance, typically require electricity from the grid for operation. The greatest amount of monetary savings is likely to occur when both system efficiency is balanced with operating costs. To do that, the objective function has to, for example, be changed from the minimization of electricity consumption to that of operating cost. However, the most cost-effective method does not necessitate the implication of the most environmentally friendly one, hence multi-objective features are required to generate Pareto frontiers, where the tradeoff between both objectives becomes explicit.

The hierarchical framework proposed in *Chapter 5* is not directly applicable for multi-period optimization problems because of two reasons - there are too many variables for the GA to manage, and the MILP becomes inconvenient to repeatedly formulate. Therefore, this chapter explores the use of the sliding-window technique to complement *Chapter 5*'s hierarchical framework for handling the two, above-mentioned shortcomings. The applicability of the proposed method is highlighted

through a case study based on the same DCS system as in the previous chapter, with the addition of a theoretical cold-water tank TES.

6.2.1 Issues arising from multi-period considerations

The primary benefit of the hierarchical framework proposed in *Chapter 5* is the capability to holistically optimize the operation of the DCS in terms of its tuneable variables. The finer level of granularity, however, calls for the optimization framework to be exposed to a greater number of decision variables and constraints, for which the direct addition of the multi-period criteria and storage models cannot be accommodated with ease. Using the storage model described in *Section 3.3.5.5*, the key issues plaguing the scalability of the *Chapter 5*'s methodology is described.

1. Number of GA decision variables

Inclusion of the storage model, means that equations such as *Equation 3.55* needs to be formulated in the optimization problem. These types of equations are needed to determine the temperature of the chilled water stored for every time-period; as shown in *Chapter 5* temperature-related variables had a significant impact on the energy performance of the DCS.

Equation 3.55 is reproduced in the following for easy reference.

$$T_{s,cold,t+1} = (1 + k_{loss}) \times \frac{T_{cold,t}^{in} \dot{m}_{1,t} + T_{s,cold,t} \frac{V_{cold,t}}{t}}{\dot{m}_{1,t} + \frac{V_{cold,t}}{t}} \quad (6.1)$$

Linearization of the above equation means that the variables $\dot{m}_{1,t}$ and $V_{cold,t}$ need to be managed by the GA. The addition of two variables not only means that the GA decision variables will be increased by 50% (*Table 5.5*), but also that the feasible search space is diminished. The addition of $\dot{m}_{1,t}$ and $V_{cold,t}$ results in a significant increase of infeasible variable combinations; for instance the selected flowrate ($\dot{m}_{1,t}$) into the tank may be larger than the tank's remaining capacity ($V_{max} - V_{cold,t}$). Given the difficulty of representing constraints in the GA, adding multi-period considerations into the formulation exacerbates the problem making the metaheuristic's search for optimality highly challenging.

2. Number of MILP constraints

The reduction of the GA variables in the hierarchical optimization framework resulted in an increase in both the number of constraints and variables in the slave-level MILP formulation. For the case study involving the DCS in *Chapter 5*, the hourly formulation required approximately 2000 constraints to be formulated. Since there were no thermal storage systems involved, it can be assumed that each time-period is independent of the next, allowing their solutions to be solved in parallel. However, where multi-period considerations are required, not only will the number of constraints be drastically increased, parallel implementations for solving the problem also becomes inconvenient to implement. A 24-hour period problem with thermal storage requires approximately 48000 constraints to be formulated. If the problem were to be solved in series with the GA's population size and generations set to be 200 and 50 respectively, this means that the 48000 constraints will have to be written 10000 times, making the resolution time excruciatingly slow.

Due to the above-mentioned issues, it is therefore not advisable to directly implement the hierarchical optimization framework onto the multi-period optimization problems where storages are involved. The sliding-window technique is thus required to reduce the size of the optimization problem, such that it still can be solved to a reasonable degree of fidelity to the real operating system.

6.2.2 Sliding-window technique

The version of the sliding-window technique used in this chapter assumes a fixed window size (m , number of time-periods, considered), which is pre-determined. Once the window size is fixed, the concomitant optimization problem is formulated for the size of the specific window and solved. However, once solved, the solution is only extracted for the first time-period of the window. Subsequently, the window will 'slide' - in doing so, it removes the first time-period and adds the next time-period, which was formerly outside, i.e. $p = m + 1$, before repeating the entire process until the full multi-period optimization problem is solved. The sliding-window technique can be better visualized through *Figure 6.1*.

FIGURE 6.1: The sliding-window technique.

The choice of the window size factors future demand conditions, when making decisions in the present, hence it has to be chosen judiciously for results to be satisfactory. Incorporating the sliding-window technique into the hierarchical framework has two primary benefits - increasing the solvability of a large optimization problem and the ability to deliver results for individual time-periods quickly.

6.2.3 State of the art

MILP is commonly deployed to solve for the optimum operation plan of urban energy systems including storages [183–185]. The highly abstract models utilized in these studies, permitted the formulation of the optimization problem as a MILP, hugely promoting solvability. These models are only capable of quantifying the energy in and out-flows; regardless of how positive the optimal results are, they suggest very little on how the system should be operated. The efficiency of urban thermal systems, in particular, are especially sensitive to temperature changes, hence optimization with respect to thermal energy flows alone is insufficient [63].

For design-related, MINLP solvers are deployed to manage the non-linearities which pertain to the sizing of the storage system [186, 187]. These studies, however, pertain to the sizing of the storage system, rather than its operation. Additionally, MINLP solvers, while capable of generating improved solutions, have no guarantee on resolution time and solution quality. For even more complex models, simulation is used [188].

Fazlollahi et al. discretized the thermal storage into several temperature bands before using a combination of evolutionary algorithms and MILP to solve for the optimal system design [92]. Despite being a design-related study, the factoring of temperature variables offers a guide on the appropriate temperatures to operate the system. Fang et al. formulated an optimization problem into a linear program for the optimization of thermal storage of a CHP plant [189]. Despite, the simplistic modeling of the CHP plant, attempts to reduce the complexity of the problem reduced through the use of the sliding-window technique. These findings show that a negligible impact on the objective function is observed, once a window size of five time-periods (days) was chosen. This effectively suggests that solving the problem in its entirety (simultaneous consideration of all time-periods) is an unnecessary endeavor - the indiscriminate use of computing resources.

It is indicative from this review that besides [189], there is little attempt to improve on the solvability of multi-period optimization besides model simplification. Where the optimization of the operations of urban energy systems is concerned, the importance of expressing the problem in terms of tuneable variables due to the insights gained on possible improvement. This still holds even with the addition of energy storage systems. In addition, there currently exists no methodology which is capable of solving multi-period optimal operation problems of energy systems using high fidelity models - hence, the current work focuses augmenting the hierarchical framework with the sliding-window technique for this very purpose.

6.2.4 Objectives

The complexity of the holistic optimization of the operations of urban energy systems is further exacerbated with the addition of storage. In this chapter, the hierarchical optimization framework in *Chapter 5* is augmented with the sliding-window technique before its successive application on a case study based on an existing DCS with a theoretical storage system. The results presented in this study aspires to accomplish two objectives - illustrate the impact of storage systems on the operation of chillers when optimized for different objectives, and discuss the effect of the window size on the objective function value.

6.3 Problem formulation

This section begins with a description of the case study, followed by the augmented optimization framework. Finally, the formulation of the accompanying optimization problem is presented.

6.3.1 Case study description

Figure 6.2 illustrates the schematic of the DCS with a theoretical storage system. It was established in *Chapter 5* that there are scenarios whereby the chilled water temperature (T_e^{out}) was lowered to prevent another chiller from starting. In an attempt to reduce the frequency of this occurrence, the storage system was added to the DCS to bridge the gap between the small and large chillers. A two-level water storage tank is chosen as the storage medium, due to economical and technology maturity reasons. Typically, either the load-leveling or load-shifting methods would have been used for sizing the tank, however, due to physical constraints in the central station of the DCS, only two tanks are considered - one, sized to the maximum tank size which the facility can accommodate, and the other, half the capacity of the former. The smaller tank is included in the case study for illustrative use, i.e., comparing the effects of the window size, etc. *Table 6.1* describes the size of the storage tanks considered.

Description	Nominal capacity	Quantity
Storage tank	1000m ³	1
	500m ³	1

TABLE 6.1: Size of chilled water tank considered in the case study.

The models of the equipment, other than the storage facility, are shown in *Figure 6.2* is identical to the system described in *Section 5.5.1*. The input conditions used are referenced from the ‘high-load’ scenario described in the same section.

FIGURE 6.2: Schematic of the cast study DCS with a theoretical two-layer storage tank.

6.3.2 Sliding-window augmented hierarchical framework

Owing to the sheer size of the optimization problem, when the TES is included, the direct application of the sliding-window technique to the hierarchical framework does little to aid solvability; i.e., even for small window sizes, the GA did not converge to any value better than the seeded one despite the many iterations it had undergone. This is likely due to the difficulty in expressing inter-period constraints at the master-level where the GA resides.

To deal with this issue, the sliding-window technique is first applied to a simplified model of the DCS, involving only the chillers, TES, and consumers. Doing so enables the pre-determination of a storage schedule before utilizing the optimization framework. This schedule, when obtained, indicates how much energy to charge and discharge for any given time-period. Finally, the schedule is assimilated as parameters in the hierarchical framework, before solving for the optimal operation plan. The overview of the augmented hierarchical optimization framework is illustrated in *Figure 6.3*.

The chiller and storage models used during the scheduling phase have discretized operating temperatures, allowing the optimization problem to be formulated as

a MILP. The consideration of varying temperature levels is done for enhanced realism; accounting for scenarios whereby more thermal energy may be required to be stored in the tank of fixed volume, even at the expense of current operating efficiencies. Doing so could benefit from the overall electricity consumption over the given period, determined by the window size. Additionally, the operating *COPs* of the chillers is discretized in this phase, for similar the same reason.

FIGURE 6.3: Overview of the sliding-window augmented hierarchical framework.

6.3.3 Mathematical formulation

This subsection deals with the mathematical formulation of the augmented hierarchical optimization framework. There are three levels in this approach - first the determination of the storage schedule, second, the master-level and lastly, the slave-level. Detailed description of the component models are not discussed here, as they can be found in *Chapter 3*.

Storage scheduling

The addition of storage systems inevitably requires multi-objective considerations. In this case, the linear scalarization technique is used to optimize the system either with respect to electricity consumption or operating cost. Both objectives are first normalized before the application of the linear weights ranging from 0 to 1. The decision variables and parameters associated with the simplified formulation used to determine the storage schedule are documented in *Table 6.2*.

Decision variables	Description
$\dot{Q}_{ch,i,t,p}$	the cooling rate provided by chiller (i) at discretized temperature (t) at time-period (p).
$Q_{scm,t,p}$	the cold energy stored at temperature (t) at period (p).
$Q_{dcm,t,p}$	the cold energy discharged at temperature (t) at period (p)
Parameters	
$\dot{Q}_{d,i,p}$	cooling demand of the i th customer substation at period (p).
T_{wb}	thermodynamic wet-bulb temperature.
$\Delta T_{ss,i}^{max}$	maximum temperature difference on the cold-side of the heat-exchanger at the substation.
k_{loss}	the hourly storage energy loss coefficient.

TABLE 6.2: Parameters and variables associated with the simplified multi-period case study.

Objective function

Given a window size (m) and weight (w), the objective function at the storage scheduling stage is defined as:

$$\text{minimize } w \sum_{p=1}^m \dot{E}_i + (1 - w) \sum_{p=1}^m C_{\dot{E},p} \quad (6.2)$$

where $\dot{E}_p$ and $C_{\dot{E},p}$ refer to the quantity and cost of electricity of each time-period within the sliding-window of size m .

Constraints

Given that the quantity and cost of electricity is a function of the cooling effect produced by the chiller ($\dot{Q}_{ch,p}$), the following constraints ensure that the customers

always have their hourly demand met.

$$\text{subject to} \quad \dot{Q}_{ch,p} + \dot{Q}_{dcm,p} \geq \dot{Q}_{d,p} + \dot{Q}_{scm,p} \quad (6.3)$$

This inequality ensures that the quantity of cold energy available during every time-period (p) is either consumed by the customers or stored. Since the quantity of energy stored during time-period p will be made available for the next period $p + 1$,

$$(1 - k_{loss})\dot{Q}_{scm,p} \geq \dot{Q}_{dcm,p+1} \quad (6.4)$$

The term k_{loss} is added to account for the hourly thermal losses for storing the chilled water.

For simplicity and to maintain compatibility with the MILP format, the temperature of chilled water supplied by the chillers are discretized and converted into energy quantities. This is done through the assumption of fixed flowrates ($\dot{m}_e$) and a maximum value of the chilled water temperature ($T_{e,max}^{out}$) can assume. For instance if $T_{e,max}^{out} = T_{e,p}^{out} = 5^\circ C$, there will be no cooling effect produced by the chiller. The purpose of these inclusions is for scenarios where the storage of additional cold energy at lower temperatures in the given time-period, could be beneficial for the given objectives, for future usage.

Finally, after the above problem for the given window size, only optimal values of $\dot{Q}_{scm,p=1}$ and $\dot{Q}_{dcm,p=1}$ are extracted. They will both be used as input values for the next set of sliding-window time-periods as well as for the hierarchical optimization framework. To determine the suitable size of the sliding-window and for multi-objective optimization, the formulation above is solved for a range of values of m and w .

Hierarchical framework

Once the storage schedule is determined, the charging mode ($\dot{Q}_{scm,p}$) and discharging mode ($\dot{Q}_{dcm,p}$) values serve as parameters. Only one of the two modes can be activated at once. During charging mode, the behavior of the storage tank is analogous to a customer, with a cooling demand of $\dot{Q}_{scm,p}$. Conversely, in discharging mode, the storage tank assumes the profile of a ‘chiller’ which consumes no electricity, delivering cold energy of $\dot{Q}_{sdm,p}$. Adding these to the equations presented

in *Section 5.5.2.1* allows for the optimal values of the rest of the components to be solved for. The following table describes the storage variable and parameter values used in this case study. The values for the remaining components can be found in *Table 5.6*.

Component	Equation	Coefficients	Variable bounds
Storage tank (small)	3.55	$k_{loss} = 0.05$	$0 \leq \dot{m}^{in} \leq 500$
Storage tank (large)	3.55	$k_{loss} = 0.05$	$0 \leq \dot{m}^{in} \leq 1000$

TABLE 6.3: Parameters and variable values for the component-level models used in the TES case study.

6.4 Results and discussion

The results presented in this section will focus on two key aspects - the impact of TES on the operation of chillers, when optimized with different objectives, and the effect of the sliding-window size on the quality of the final solution. Discussion pertaining to holistic optimization and the effect of storage systems on ancillaries are not included as they revolve around similar explanations as those presented in *Chapter 5*.

6.4.1 Effect of TES on chiller operation

Figure 6.4 compares the quantity of cold energy stored in the tank across 24-hours when the DCS with TES is optimized for three different objectives. The system is optimized for minimal electricity consumption and operating cost in the first and third cases respectively. For the second case, it is balanced for the first and third objectives. The results shown in the plot are further broken down into three discrete temperature bands for which $T_1 > T_2 > T_3$ and plotted against the prevailing electricity prices. The plots in this subsection are optimized using a window size of 24 hours.

As seen in the graph, the gradual increase in the importance of operating costs in the objective function results in the optimizer choosing to store more energy in the storage system. This observation becomes more pronounced from 0600 to 0800 hours when the sharp increase in the quantity of cold energy stored in the tank corresponds to the price hike. The optimizer even chose to exceed the design

capacity of the tank (at a fixed ΔT), by lowering the temperature of the water stored. This is likely done to make more energy available during periods of high electricity prices. Similar observations are made from 1700 to 1900 hours, although to a smaller extent.

At the opposite end of the spectrum where electricity consumption is minimized, there exists a comparatively low proclivity to utilize the storage system due to losses. Thermal losses, when chilled water is stored for a prolonged period manifests itself in terms of temperature degradation. When chilled water heats up, it loses the capacity to fulfill its task of space cooling. Storage, from a pure energy efficiency perspective, wastes energy in this case.

The reason the storage system is still utilized despite optimizing solely for electricity consumption is shown in *Figure 6.5*. It can be seen from the plots that the larger chillers are never operated; cooling demand is exclusively fulfilled by the small chiller and the storage system. Due to the deficit between the design and operation conditions of the DCS, much of the cooling demand falls between the gap of the small and larger chillers. Operating a large chiller at low part-loads is highly inefficient as it contributes to the infamous ‘low ΔT syndrome’ (*Appendix C*). The choice not to operate the larger chillers suggests that the system is better off operating in spite of thermal losses.

FIGURE 6.4: Comparison of cold energy stored across 24-hours, when optimized for different objectives.

FIGURE 6.5: Comparison of cold energy supply across 24-hours, when optimized for different objectives.

6.4.2 Effect of sliding-window size

Figure 6.6 shows the evolution of the Pareto frontier as the sliding-window size (j) is increased. It is no surprise that a larger window size results in a more comprehensive exploration of the solution space. This is evidenced by the length of the frontier growing from a single point as the number of window sizes increases. With the window size of a single time-period, the optimizer is only concerned in determining the best operating condition for the current condition, hence a single point. The size of the sliding-window enables the optimizer to take into consideration future conditions while optimizing for the current time-period; the greater this consideration, however, also vastly increases the resolution time of the algorithm. For instance, the average resolution time increases exponentially from 2 to 143 seconds as the window size increases from 1 to 24. Depending on the objective, which the system is optimized for, it is unnecessary to utilize any window larger than five as the increase in cost savings falls below 1% thereafter. The same can be said for any window size larger than eight where the minimization of electricity consumption is concerned.

When the size of the storage system is reduced, the corresponding size of the sliding window is also lowered (Figure 6.7). This is due to the inability of the storage system to accumulate energy due to capacity constraints.

FIGURE 6.6: Pareto frontier evolution with sliding-window size, for large TES.

FIGURE 6.7: Pareto frontier evolution with sliding-window size, for small TES.

6.5 Conclusion

The sliding-window technique has been used to augment the hierarchical framework in this chapter. In doing so, the framework is equipped to manage the multi-period and multi-objective optimization problems that are presented by the addition of storage systems. The size of the sliding-window is a critical parameter that has to be pre-determined. It is likely to be concurrently affected by a myriad of factors such as storage capacity, hourly electricity price, demand profiles, etc. Currently, it is determined by iterating through all possible combinations until the change in objective functions become negligible. A more systematic method of doing so will add value to this implementation.

Chapter 7

Towards real-time holistic optimization

7.1 Overview

The holistic optimization of an urban energy system is a computationally intensive undertaking, owing to the sheer number of conflicting decision variables and the non-convex nature of the problem. This is the primary reason which inhibits the deployment of optimization algorithms for the real-time optimization of operations. To improve the solvability of the complex MINLP, the hierarchical framework was introduced in *Chapter 5*. However, the framework largely depends on the GA to handle non-linear variables. The GA, being a population-based metaheuristic, required many iterations of the MILP sub-problem to converge. This results in pro-longed resolution times, making *Chapter 5*'s implementation of the hierarchical framework unsuitable for real-time deployment.

To overcome this flaw, the GA is replaced by a RL in the framework. This version of the hierarchical framework, by virtue of the RL, enables the heavy computation required to optimize the non-linear variables to be shifted offline. Once sufficiently trained, only one iteration of MILP is required to be solved in real-time. The MILP assumes a similar function as it did with the previous version (with the GA) - it drastically reduces the solution space which has to be optimized by the RL, thereby promoting resolution speed and solution quality.

³The work in this chapter has been published in [190]

In this chapter, the limitations in the existing literature pertaining to the use of RL for optimization in the domain of urban energy systems are first discussed. Subsequently, the RL-MILP optimization framework is presented. *Section 7.4* compares the results of two versions of the hierarchical framework - RL-MILP and GA-MILP. The case study used in this chapter is a scaled-down version of the DCS that is presented in *Chapter 5*. The methodology presented in this chapter has been published in [190]

7.2 Introduction

This chapter explores the use of RL for the optimization of the operations of a DCS through a case study. The DCS considered in this chapter is a scaled-down version of *Chapter 5*'s. Despite that, the objective of the case study is still met as it only serves as a platform for comparison between the RL-MILP and GA-MILP hierarchical frameworks.

7.2.1 Reinforcement learning

RL is a generic machine learning technique which involves an agent taking **actions** in an **environment** and thereby earning a **reward** for it. The goal of the agent is to maximize the cumulative reward by iteratively improving on the actions taken. Typically, a NN is embedded in the agent, hence, the **reward**, which the agent receives from taking an **action** functions as a pseudo-error which is used to update the weights of the NN. This **action** - **reward** - **state** loop, thus progressively improves the predictive ability of the embedded NN, hence resulting in better actions taken each time. The typical implementation of a RL is shown in *Figure 7.1*.

7.2.2 State of the art

The successful deployment of RL in playing games (Go [191], Atari [192]) and image recognition [193] marks the most significant progress in recent history. Despite the progress, it is essential to note that most of these studies deal with discrete state

FIGURE 7.1: Typical implementation of a RL.

and action spaces which is not directly compatible with those requiring continuous state and action spaces [194]. Naive discretization of the state or action space leads to the curse of dimensionality that makes solving intractable. Thus, a class of RL algorithms known as deterministic policy gradients (DPG) has been introduced [195].

As a technique for optimal control, RL is rapidly gaining traction in the closely related field of building energy control [196], [197]. Examples of such applications include the optimization of energy performance or operating cost in HVAC systems, domestic hot water (DHW) and data center cooling, through the manipulation of temperature setpoints. Since these problems mainly involve continuous state and action spaces, deterministic methods have been employed [27, 197]. These implementations typically use end-to-end model-free approaches which only deal with the optimization of a small set of actions (decision variables). There is however no indication that the optimization of the small action space will yield optimal performance of the overall system. Training stability and convergence are other major issues that plague the performance of RL in these domains; hence techniques such as recurrent neural networks, experience replays, pretraining the neural networks with copious buffers of offline traces and guidance through expert-defined policies were some of the measures adopted mitigate these issues. Currently, there exist no methodologies, let alone RL-based ones, which are capable of performing holistic optimization of urban energy systems. This is likely because of the vast difference in size between the action and state spaces, which is the primary issue this chapter will address.

7.2.3 Objectives

Holistic optimization of urban energy systems itself presents a challenging task as a myriad of decision variables must be simultaneously optimized while respecting the tight-coupling between the components of the system and non-linearities in the governing equations. This chapter seeks to improve the applicability of the hierarchical framework presented in *Chapter 5* by replacing the GA with an RL. Through a case study based on an existing DCS, the results of the RL-MILP and GA-MILP optimization frameworks are compared for their resolution speed and solution qualities.

7.3 Problem formulation

The discussion in this section will take the following shape - first, the case study is defined, before the implementation of the RL-MILP optimization framework.

7.3.1 Case study description

The case-study *Figure 7.2* is a scaled-down version of that presented in *Chapter 5*, based on a functioning DCS located in Europe. Cooling towers were omitted, due to their negligible contribution to the objective function. By removing the cooling towers, the assumption that flowrate on the condenser side of the chiller, $\dot{m}_c$ is constant and the inlet temperature, T_c^{in} , is always $5^\circ C$ above the thermodynamic wet-bulb temperature, T_{wb} .

Since the objective of this case study only to act as a means of comparison between the two versions of the optimization framework, slight deviations from actuality are justified. The objective function defined in this case study is to utilize the RL-MILP and GA-MILP approach to optimize the electricity consumption ($\dot{E}_{DCS}$) for the given combination of cooling demand $\dot{Q}_{d,j}$ and ambient wet-bulb temperature T_{wb} . *Table 7.1* documents the parameters and the variables associated with the scaled-down case study.

Cooling demand for a single representative day is used to validate the performance of the two versions of the optimization framework. This representative day corresponds to the ‘high-load’ scenario described in *Figures 5.7* and *5.7*. The quality of the optimal objective function and resolution speed will be the metric for measuring the performance of both methods.

FIGURE 7.2: Schematic of the scaled-down DCS.

7.3.2 GA-MILP approach

In *Chapter 5*, after choosing the appropriate models, the optimization problem was decomposed into two levels - the master (GA) and the slave (MILP). Doing so, leveraged on the capabilities of MILP to increase the likelihood of converging to the

Master level: GA variables/ RL states	Description
$T_{dist,nwk}^{out}$	temperature of return fluid from the distribution network entering the evaporator side of chillers.
$\dot{m}_{sys}$	total evaporator/distribution network flowrate.
Slave level: MILP variables	
$\% \dot{m}_{e,i}^{out}$	percentage of total flowrate through the i th chiller evaporator.
$T_{e,i}^{out}$	fluid temperature exiting i th chiller evaporator.
$T_{c,i}^{out}(K)$	fluid temperature exiting i th chiller condenser.
$\% \dot{m}_{c,i}^{in}$	percentage of total flowrate through the i th chiller condenser.
$\% \dot{m}_{cp}$	percentage of total flowrate through the common pipe.
$\% \dot{m}_{ss,i}$	percentage of total flowrate through the i th customer's substation.
$\dot{m}_{a,ct,i}$	inducted air flowrate through each cooling tower.
$Pump_{sel}$	the choice/combination of distribution pump(s).
Parameters	
$\dot{Q}_{d,i}$	cooling demand of the i th customer substation.
T_{wb}	thermodynamic wet-bulb temperature.
$\Delta T_{ss,i}^{max}$	maximum temperature difference on the cold-side of the heat-exchanger at the substation.

TABLE 7.1: Parameters and variables associated with the scaled-down case study.

globally optimal solution. When the case study was formulated, only two decision variables remained as master-level decision variables ($\dot{m}_{sys}, T_{dist,nwk}^{out}$), whilst the rest could be optimized by the MILP. Implementation of the GA meant that numerous iterations of the MILP need to be undergone just for the optimum values of these two variables to be determined. A typical run of the MILP solver takes under 5 seconds to solve, which is considerably rapid, considering that it computes the optimal values to be used over a time-period of an hour. However, coupling the MILP with the GA greatly retards the entire optimization process. Should the relationship between the two master-level decision variables ($\dot{m}_{sys}, T_{dist,nwk}^{out}$) and the optimal electricity consumption be pre-determined, the feasibility of holistic optimization in real-time will be vastly improved, as only a single iteration of MILP is required. This underpins the motivation for replacing the GA with the RL.

7.3.3 RL-MILP approach

From the literature review, it appears that the primary reason that RL is used for optimization is because complex relationships between the input parameters (*state*) and the decision variables (*actions*) can be determined offline. Once

the agent is trained, solutions can be delivered almost instantaneously. However, the studies reviewed revealed that RL techniques are often only applied for the optimization of a small subset of the tuneable decision variables. This is likely done to ensure that the (**state**) always remains larger than the (**action**) space, increasing the likelihood of convergence of the NN which resides in the agent. In doing so, the significant benefits of holistic optimization, as shown in *Chapter 5* is disregarded. The combination of the RL together with the MILP solves this problem, since the latter reduces that (**action**) space of the RL such that the **state** to **action** space ratio becomes favorable for convergence. The combination of the RL and MILP makes the holistic optimization of urban energy systems in real-time possible.

The first step toward utilizing RL is to formulate the problem as a Markov decision process (MDP), with the proper definition of the **environment**, **reward**, **state** and **action** spaces. With the assumption that the actions taken in each hourly time-period is independent from the next (absence of storage systems), the optimization problem can be formulated in the similar fashion as the classic multi-armed contextual bandit problem - the only difference being continuous state and action spaces [198]. Hence, the GA was replaced with a variant of the deep deterministic policy gradient (DDPG) algorithm [194], however, instead of a **reward**, a **penalty** was introduced to discourage the agent from making poor decisions. Without using the decomposed approach, the subsequent RL problem may be difficult to solve, since the **action** space is very large in comparison to the **state** space. *Table 7.2* details the definition of the MDP in the proposed RL-MILP approach. In RL, **state**, **action** and **reward** is akin to parameters, decision variables and objective function in traditional optimization terms.

State	$\dot{Q}_{1-4}, T_{wb}$
Action	$\dot{m}_{sys}, T_{dist,nwk}^{out}$
Environment	<i>MILP</i>
Penalty	$\dot{E}_{DCS}$

TABLE 7.2: Definition of the MDP in the RL-MILP approach.

A modified actor-critic algorithm is chosen for implementation as the RL design. The job of the actor is to determine a policy for which it will always take the best **actions** for any given **state**. The job of the critic is to determine the value of the current **action** and **state** pair. This very important as some **states** have lower ‘**penalty** potential’ than others; for instance, if the cumulative cooling demand $\dot{Q}_d$

is low, the cost of electricity is likely equally low and hence must be taken into account when together with scenarios with high $\dot{Q}_{ds}$. This is why the actor-critic algorithm is selected over generic policy-based methods. By taking the **actions** and **state** as inputs, the critic can estimate the expected **penalty**. Should the **penalty** be lower than expected, the critic will send a positive signal through the Q-value to the actor. A lower Q-value is analogous to a smaller error to be back-propagated in NN terms, thus maximizing the probability that the actor takes such **actions** for these given **states**. The error incurred by the critic comes from measuring the difference between the expected and actual **penalties**. Exploration is taken care of in the programming of the actor NN training algorithm, where there is a predefined probability (ϵ) that the actor takes a random **actions** other than those prescribed by the trained NN. This is done in the hope that it may randomly chance upon a better set of **actions** which will result in lower **penalties**.

Figure 7.3 illustrates the implementation of the forward-feed neural network architecture and Figure 7.4 summarizes the proposed implementation of the RL-MILP approach. For the actor neural network, the hidden layer is defined to output four values - two mean (μ) and two sigmas (σ) values which were then used with the normal distribution function to generate the probabilistic values for the **actions** output layer. Subsequently, the losses of the neural networks are reduced using the Adam optimizer, with learning rates of 0.001 and 0.0001 for the actor and critic network respectively [199]. Finally, to discourage the weights of the NN to converge towards local optima, the exploration epsilon (ϵ) is set to 0.01. Algorithm 1 details the training procedure used to update the weights for the neural networks.

7.4 Results and discussion

In this section, the results of the holistic optimization of DCS operations derived from the GA-MILP and RL-MILP approaches are compared from two perspectives - solution quality and resolution speed. Details pertaining to the behavior of the decision variable values at the optimum will not be presented, since they have been discussed at length on a very similar case study presented in Chapter 5. For a given set of master-level decision variables, the performance at the slave-level MILP will perform in the similar manner, making the relationship between the former and the objective function (**reward**) one-to-one. The primary purpose of comparing

FIGURE 7.3: Neural network architectures.

Algorithm 1: Training algorithm for the actor-critic neural networks.

1. Collect the hourly state data over the period of 1 month. The *penalties* refer to $\dot{E}_{DCS}$ which is an output from the *environment*.
2. Select 1 day outside the training data trace to be used for validation.
3. Initialize neural networks $a(X_{act}|\theta^{act})$ and $c(X_{cri}|\theta^{cri})$ with weights initialized using the Kaiming initialization scheme [200].
4. **for** $j = 1, \dots, \text{max episodes}$ **do**
 - (a) Compute $\delta_{cri,j} = (c(X_{cri,j}|\theta^{cri}) - \dot{E}_{DCS,j})$
 - (b) Update θ^{cri} by minimizing $\delta_{cri,j}^2$
 - (c) Compute $\delta_{act,j} = -\log(\mathcal{N}(a(X_{act,j}|\theta^{act}))) \times \delta_{cri,j}$
 - (d) Update θ^{act} by minimizing $\delta_{act,j}$

end for

FIGURE 7.4: Summary of the RL-MILP approach.

the solution quality is to investigate how does the RL-MILP approach fare against the GA-MILP approach, given that the GA is should generally perform better for non-linear optimization problems.

7.4.1 Solution quality

Figure 7.5 compares the $\dot{E}_{DCS}$ values generated for the validation data-trace using both approaches against the ‘base’-case. After training the RL for 3000 episodes, significant savings in electricity consumption can already be noticed, when compared against the ‘base’-case. Although the GA-MILP approach generally performed better, there exist scenarios whereby it was outperformed by the RL-MILP, such as in the 1st, 5th, and 17th hour. One possible explanation for this observation is the advantage gradient descent optimizers have over the GA when searching for local optima. The converse is true especially in the 12th and 22nd hour where it

is likely that the optimizer used to minimize the losses in the NNs (Adam) had trouble escaping local optimums.

Table 7.3 documents the percentage difference of $\dot{E}_{DCS}$ of the ‘base’-case, GA-MILP and RL-MILP approaches over 3000 episodes. The accuracy generally improves with the number of training episodes. Beyond 3000 episodes, however, the performance on the validation trace started to degrade. Overfitting to the training data traces could be a possible reason for this observation. Another explanation could pertain to the inability to fully capture the relationship between the **states** and **sactions** within the current size and architecture of the neural networks. Where escaping local optima are concerned, off-policy methods could also be explored.

7.4.2 Resolution speed

This is where the primary benefit of the RL-MILP approach lies. The average time is taken to solve the MILP sub-problem ranges from approximately 3-5 seconds. The GA-MILP required about 15 000 evaluations of the MILPs to converge for a single time-period of length one hour. Despite only having undergone 3000 MILP evaluations, the absolute difference in electricity savings between the GA-MILP and RL-MILP approaches is only 7.52%.

Since the RL is trained offline, real-time performance will not be impeded, regardless of the number of training episodes it required to converge to a reasonable value. When properly trained, a single evaluation of the MILP is all that is need to deliver the optimal values of all the decision variables required to operate the DCS efficiently.

Episodes	Percentage difference (RL-MILP vs ‘base’-case)	Percentage difference (GA-MILP vs ‘base’-case)
1000	-3.92	-34.36
2000	-23.68	
3000	-26.84	
4000	-22.55	

TABLE 7.3: Comparison of differences in $\dot{E}_{DCS}$ between the ‘base’-case, GA-MILP and RL-MILP approach over 3000 episodes.

FIGURE 7.5: Plots of $\dot{E}_{DCS}$ for the ‘base’-case, GA-MILP and RL-MILP (after 3000 episodes) approaches.

7.5 Conclusion

Through the use of RL and MILP in the hierarchical optimization framework, the majority of the heavy computation needed to determine the optimal values of the non-linear decision variables could be shifted offline. This vastly improved the feasibility of the hierarchical framework for real-time holistic optimization applications. When the reinforcement learner was trained, it generated close to optimum solutions almost instantly, a feat which was impossible with the previous version of the framework, involving the GA.

Accounting for stochasticity in demand and improving the optimization capabilities of the RL are two areas that will vastly add value to the current implementation.

Chapter 8

Conclusion and future work

8.1 Overview

The key contributions of this thesis and suggestions for furthering the current work are presented in this chapter. *Section 8.1.1* presents a summary of this thesis. The open problems and short comings of this thesis, which provides directions for further research on the optimization of urban energy systems, is discussed in *Section 8.1.2*.

8.1.1 Conclusions

The incongruity between design and operating conditions of urban energy systems will always persist due to imperfection in available data for the forecast of future conditions. This results in the potential of urban energy systems being hardly realized. To address this deficit, a framework for the holistic optimization of the operations of urban energy systems has been proposed in this thesis. This framework is comprised of an amalgamation of techniques, ranging from model abstraction to reinforcement learning with the goal of simultaneously achieving two objectives - holistic optimization of the system while maintaining solvability of the concomitant optimization problem. The importance of the former cannot be overstated, due to the high level of interdependence amongst the components of an energy system. Localized optimization categorically denies this, unnecessarily pruning the already restricted solution space for problems concerning operations.

Related studies on the optimization of urban energy systems often deploy highly simplified models, which offer little guidance on the improvement of operations [21, 22]. Two essential criteria have to be met for the results of these studies to be useful - the expression of decision variables that are tuneable and the modeling of the interdependencies amongst system components. These requirements demand for models of higher fidelity; which inevitably complicates the optimization problem. Chapter 4 addresses this issue through the use of abstraction techniques on judiciously selected component-level models from the existing literature. This endeavor permitted energy systems to be adequately modeled whilst keeping the problem formulation within the realms of a mixed-integer linear program, thereby ensuring solvability.

Since abstraction techniques alone are insufficient, a hierarchical framework was introduced in Chapter 5 to complement. This framework utilizes the combination of the genetic algorithm and mixed-integer linear program solver for the optimization of operations. The genetic algorithm was introduced to optimize crucial decision variables of the abstracted models which cannot be linearized. The existence of the mixed-integer linear program aids the metaheuristic by reducing the metaheuristic's search space, thereby benefiting resolution speed and the likelihood that global optimality is obtained.

The inclusion of energy storage systems further compounds the problem's complexity, given the necessity for multi-period and multi-objective optimization. Burgeoning sizes and intractability of optimization problems are a consequence when the above-mentioned requirements are simultaneously considered with high-fidelity models. To enhance the solvability of such problems, the hierarchical optimization framework was augmented with the sliding-window technique in Chapter 6. The right selection of the window size, drastically improved solvability and gave a good approximation of the optimal solution. This effectively suggests that solving the problem in its entirety is an unnecessary waste of computational resources.

Genetic algorithms are population-based metaheuristics that utilize iterative methods to derive solutions. Substantial resolution times are a ramification of its use - the primary reason which inhibits the real-time applicability of the proposed optimization framework. To address this issue, the genetic algorithm was replaced with a reinforcement learner in Chapter 7. This measure enabled the heavy computation required to optimize the non-linear decision variables to be shifted offline.

Once sufficiently trained, only a single iteration was required for solving the mixed-integer linear programming sub-problem to deliver close-to-optimal solutions. This version of the hierarchical framework justifies the approximate solutions through drastic improvements in the real-time resolution speeds.

Finally, the use of these techniques across the various chapters has been individually validated through applications on case studies on existing urban energy systems. Results indicate cost and energy-saving potentials of up to 12.7% and 35% respectively. Thus, the work in this thesis has successfully addressed the problem statements which were identified in *Chapter 1*.

8.1.2 Suggestions for future work

The contributions of this thesis only address a small part of the inexhaustible list of issues which plague the efficient operation of urban energy systems. Three key issues which have arisen from the shortcomings of the current work are discussed in this subsection, to provide directions for furthering this research.

Modeling Techniques. The applicability of the hierarchical framework developed through the course of this thesis hinges on the quality of the model choice. A model that encapsulates greater details will inevitably also complicate the ensuing optimization problem. Hence, it is paramount to determine and expand on a set of representative models that offer a good balance between fidelity and solvability. It is evident from the review of the state of the art that there exists a knowledge-gap between mathematicians and engineers - through the indiscriminate use of optimization techniques on commercial simulation tools.

The models selected to represent components in the case studies still leaves much to be desired. Network delays, for instance, is one important feature that is absent. This is an especially important aspect for district-level thermal systems as it could take a considerable amount of time for the water from the central station to reach the customer. Not taking that into account risks the possibility of voiding the validity of the ‘optimal’ solution. The likelihood of such an occurrence will only increase when the granularity of time-periods is reduced - a desired feature of fast response real-time control systems. A model that captures this phenomenon

exists in literature, however, research on optimization compatibility has yet to be embarked on [201, 202].

Optimization techniques. A closely related topic as a direct consequence of modeling techniques. The deployment of highly abstract models permits the use of better, more robust convex optimization techniques with expeditious resolution times and strong guarantees of global optimality. The heavy reliance on meta-heuristics to derive some form of ‘enhanced’ solution on simulation tools is currently, the state-of-the-art. More should be done to address this issue, such as the hybridization of mature optimization techniques with less conventional approaches such as machine learning. One example could be the coupling of reinforcement learning with robust optimization approaches, to further the work presented in the *Chapter 7* of this thesis.

Another key aspect concerns the assumption that all interacting components within the system have perfect information about each other. This is typically untrue when the complexity of systems present challenges to the relevance of centralized optimization techniques. Deployment of distributed optimization techniques have since gained traction in the field of unit-commitment power generation and should be extended for general energy-related problems [203].

Handling of uncertainties. The overwhelming majority of the optimization studies reviewed in this thesis utilize deterministic methods. This effectively disregards the impact of uncertainties in the derivation of the optimum. Only a handful of preliminary studies forays into the impact of uncertainties in the input parameters at the design level [86–88]. However, these algorithms may not be suitable for real-time operation optimization due to substantial computational requirements. Sensitivity analyses have also been applied to highlight the effect of uncertainties on the optimal solutions [93]. These methods, however, can only serve as a cautionary role on the viability of the solution in the post-processing phase, as they do nothing to influence the derivation of the optimum.

The tool which this thesis aspires to construct is hugely dependent on input parameters such as energy demands which is by no conceivable means, deterministic in nature. This holds regardless of how accurate predictive algorithms may be. Such considerations threaten to completely transform the optimization landscape - a well-established wisdom in the field of stochastic optimization.

Appendix A

Parameters and coefficient values of the example models used for verifying abstracted models

The coefficients used for plotting for building the example models chosen in *Chapter 3* before they were abstracted are shown in the following table. In addition, the lower and upper bound of the variables used to generate *Figures 3.4, 3.8, 3.20* and *3.24* and also included. The data which was used for deriving these coefficients, however, is withheld for confidentiality reasons given, under the instruction of the collaborators.

Component	Equation	Coefficients	Variable bounds	Remarks
Heat pump	3.1 3.2 3.4	$\beta_0 = 0.1230$ $\beta_1 = 1044.7973$ $\beta_2 = 0.0204$ $\alpha_0 = 1.0980$	$200 \leq \dot{Q}_e \leq 2000$ $25 \leq T_c^{in} \leq 30$ $108.6951 \leq \dot{m}_e \leq 217.3903$ $3 \leq T_e^{out} \leq 5$	Function of T_{wb}
Cooling tower	3.21 3.23 3.24	$\beta_0 = 0.1402$ $\beta_1 = 0.6002$ $\beta_2 = -0.0211$ $\beta_3 = 0.2792$ $\beta_4 = 9.2946$ $\beta_5 = 0.1605$ $\alpha = 2.3294$ $\gamma = 0.000059601$	$407 \leq \dot{m}_{ct}^{in} \leq 3359$ $27 \leq T_{ct}^{in} \leq 35$ $0 \leq \dot{m}_a^{in} \leq 369117$	
Pump and network	3.28 3.32	$\alpha = 1.9115$ $\beta_0 = 0.0945$ $\beta_1 = 1.4109$	$0 \leq \dot{m}_{sys} \leq 1700$ $0 \leq \Delta P_{op} \leq 75$	
Water-to-air heat exchanger	3.43 3.44 3.45 3.46	$Cf = 1$ $A = 87.5083$ $U = 0.4000$ $\alpha_0 = 0.05750$	$28 \leq T_a^{in} \leq 35$ $25 \leq T_w^{in} \leq 30$ $7 \leq \dot{m}_w \leq 28$ $178500 \leq \dot{m}_a \leq 179000$	Function of T_{amb} Function of T_{wb}

TABLE A.1: Table of parameters and coefficient values of the example models used for verifying abstracted models.

Appendix B

Hydraulically decoupled cooling system

The terms ‘primary’ and ‘secondary’ networks used in this section differ from those used in the rest of the report. The term ‘secondary’ network used here is analogous to the ‘distribution’ network in preceding sections. The nomenclature is as such due to the adaptation of ‘building-level’ concepts for thermal energy systems. *Figure B.1* illustrates a typical piping scheme of this nature, for chilled water systems (heat pump operated as chillers).

The primary-secondary water piping scheme was conceived as a result of heat pumps’ inability to accommodate high flowrate fluctuations at the condenser/evaporator side. Control of thermal exchange at the demand side is important and typically done through adjustment of the water flowrates. As a compromise, the common-pipe is introduced to enable the ‘short-circuiting’ of water from the outlet of the condenser/evaporator to the inlet. Older systems cannot control temperature by varying flowrates, thus reheaters, etc., are used instead, resulting in more energy expended. The flexibility of flowrate control despite the limitations of heat pumps is the main benefit of this design [204].

Respective pumps determines the flowrate in each network independently. Flowrate in the common pipe could go either direction, depending on the difference in flowrates in either of the networks. The mixing of water from the common pipe with the supply/return water needs to be managed properly. Excessively low/high

return water temperatures to the heat pumps will impede the heat pumps' capacity to deliver the required cooling/heating and gives rise to a myriad of problems associated with 'low ΔT syndrome'. Recirculation of return water will conversely degrade supply water temperatures in addition to wasting energy.

FIGURE B.1: A typical primary-secondary hydronic system, for chilled water distribution.

Appendix C

Low ΔT syndrome

Low ΔT syndrome occurs when the temperature difference across the condenser/evaporator side of the heat pump is small.

If the return water temperature to the heat pump is not sufficiently high, the ability of heat pumps to cool down/warm up the water will be impeded. Heat transfer is highly dependent on temperature difference, thus negatively impacting the efficiency of heat pumps. For the same quantity of thermal load required, a small temperature difference would imply high flowrates and increased electricity consumption of pumps.

Changes in thermal loads present a whole new set of issues. Once the system is insensitive to variation of flowrates as a control measure, very large changes in flowrates will have to be made to accommodate small changes in thermal loads. As a result, additional heat pumps (due to flowrate limitation) and pumps will have to be activated. This happens despite not fully loading the currently operating heat pumps [205].

Appendix D

Input data for the ADREAM case study

The input data pertaining to the selected typical day for each month is documented in the following tables.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	1.27	0.0	0.0	7.583	3.835	8.389
1	3.061	5.68	2.255	1.902	8.189	3.31	8.421
2	3.051	5.736	2.281	1.913	7.993	2.888	8.325
3	3.058	5.822	2.323	1.943	7.886	2.589	8.247
4	3.012	5.763	2.309	1.925	7.487	2.431	8.482
5	3.031	5.871	2.363	1.969	7.465	2.429	8.598
6	11.361	36.11	16.785	12.776	7.822	2.581	8.553
7	7.89	29.283	11.148	12.155	7.396	2.877	33.307
8	13.329	32.949	16.114	14.568	7.517	3.31	130.934
9	7.623	21.039	11.191	13.563	7.639	3.871	276.921
10	7.717	19.313	10.747	13.463	6.793	4.551	266.922
11	6.656	16.562	9.335	12.052	2.163	5.341	208.284
12	5.286	13.588	7.694	10.521	0.0	6.234	236.773
13	4.614	14.785	8.409	9.472	0.0	7.22	187.96
14	4.109	9.836	6.041	9.199	0.0	8.248	142.47
15	4.202	8.936	5.596	9.079	0.0	9.089	102.251
16	4.545	9.027	5.748	9.198	0.0	9.475	28.157
17	4.975	9.783	6.118	9.144	0.43	9.2	8.588
18	5.495	13.658	8.314	8.514	1.552	8.421	8.45
19	10.766	20.978	11.76	10.074	3.014	7.415	8.482
20	10.745	21.289	11.476	9.994	4.14	6.431	8.508
21	5.676	15.724	5.946	7.243	4.911	5.55	8.64
22	1.058	0.0	0.0	0.0	5.69	4.772	8.564
23	1.091	0.272	0.0	0.0	6.731	4.101	8.493

TABLE D.1: Input data for a typical day in the month of January.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	0.881	0.0	0.0	6.801	4.905	8.349
1	3.061	4.082	1.895	1.419	6.6	4.26	8.219
2	3.051	3.863	1.716	1.69	7.036	3.725	8.374
3	3.058	3.608	2.012	1.508	5.938	3.325	8.425
4	3.012	4.036	1.587	1.527	5.016	3.086	8.443
5	3.031	4.728	2.024	1.35	5.332	3.03	9.702
6	11.361	28.143	11.779	9.286	6.812	3.165	34.313
7	7.89	19.207	8.234	9.654	5.61	3.478	88.357
8	13.329	27.338	13.918	13.586	6.059	3.956	209.342
9	7.623	16.277	10.772	11.803	6.852	4.587	273.349
10	7.717	14.064	8.357	13.14	6.017	5.359	751.243
11	6.656	12.802	8.043	10.79	2.121	6.257	1157.28
12	5.286	10.023	7.094	9.768	0.0	7.271	2132.64
13	4.614	11.826	6.659	8.943	0.0	8.36	461.814
14	4.109	6.69	5.617	8.255	0.0	9.397	1394.539
15	4.202	6.647	4.728	9.094	0.0	10.232	779.683
16	4.545	6.301	4.327	7.738	0.0	10.718	57.876
17	4.975	8.552	5.164	6.743	0.364	10.713	8.695
18	5.495	8.703	6.766	6.162	1.444	10.217	8.613
19	10.766	15.715	8.341	8.904	2.523	9.377	8.539
20	10.745	16.015	8.177	7.262	2.87	8.344	8.673
21	5.676	11.459	4.387	5.158	3.669	7.27	8.555
22	1.058	0.0	0.0	0.0	4.677	6.284	8.563
23	1.091	0.212	0.0	0.0	5.085	5.419	8.463

TABLE D.2: Input data for a typical day in the month of February.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	0.844	0.0	0.0	6.315	5.193	8.278
1	3.061	2.837	1.494	1.183	4.211	5.49	8.345
2	3.051	2.004	1.235	1.032	3.764	6.087	8.246
3	3.058	1.704	0.889	0.726	2.573	6.863	8.605
4	3.012	1.539	0.662	0.52	2.132	7.698	9.673
5	3.031	1.519	0.595	0.568	2.233	8.543	84.807
6	11.361	9.605	4.695	3.675	2.335	9.407	347.915
7	7.89	7.583	2.72	3.282	1.77	10.302	973.554
8	13.329	7.315	5.249	4.766	2.354	11.238	1340.54
9	7.623	4.905	3.551	4.039	2.716	12.227	2209.753
10	7.717	4.904	4.055	4.738	2.055	13.271	3092.634
11	6.656	5.587	3.747	3.92	0.901	14.129	1085.047
12	5.286	4.277	3.517	4.927	0.0	14.309	1140.667
13	4.614	6.52	3.828	5.431	0.0	13.66	527.757
14	4.109	5.201	3.788	6.586	0.0	12.615	163.691
15	4.202	6.666	4.661	7.728	0.0	11.544	145.629
16	4.545	6.613	4.571	7.235	0.0	10.507	64.233
17	4.975	8.901	5.464	8.583	0.469	9.513	10.426
18	5.495	10.866	7.699	9.389	1.31	8.571	8.559
19	10.994	15.701	10.95	8.33	3.332	7.691	8.521
20	10.745	16.75	12.012	8.598	4.4	6.883	8.537
21	5.676	12.152	5.261	6.423	3.825	6.177	8.578
22	1.058	0.0	0.0	0.0	5.187	5.627	8.493
23	1.091	0.167	0.0	0.0	4.769	5.288	8.421

TABLE D.3: Input data for a typical day in the month of March.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	0.352	0.0	0.0	2.548	10.766	11.167
1	3.061	1.195	0.753	0.589	2.404	9.77	10.187
2	3.051	1.491	0.824	0.556	2.782	8.894	9.713
3	3.058	1.258	0.631	0.641	2.266	8.188	9.373
4	3.012	1.185	0.739	0.545	2.267	7.7	9.154
5	3.031	1.175	0.855	0.621	2.56	7.481	12.1
6	11.361	8.432	5.222	4.327	2.818	7.567	112.453
7	7.89	6.812	4.587	4.091	2.824	7.94	329.486
8	13.329	8.27	5.596	5.824	3.34	8.558	570.215
9	7.623	5.483	4.413	5.341	2.901	9.379	1186.01
10	7.717	6.43	5.072	6.724	2.695	10.364	2177.389
11	6.656	5.111	3.753	5.621	0.914	11.469	3390.677
12	5.286	4.828	3.895	4.797	0.0	12.654	3666.037
13	4.614	4.653	4.767	4.81	0.0	13.87	3633.439
14	4.109	4.129	3.566	4.336	0.0	15.02	3302.605
15	4.202	3.882	3.031	5.002	0.0	15.993	2670.914
16	4.545	3.703	3.476	5.204	0.0	16.678	1970.913
17	4.975	3.239	2.944	5.307	0.258	16.964	1158.522
18	5.495	5.182	3.787	4.227	0.741	16.765	457.244
19	10.766	7.274	5.363	4.014	1.281	16.146	48.06
20	10.745	5.847	4.385	4.451	1.722	15.223	13.565
21	5.676	4.762	2.366	2.487	1.984	14.114	13.16
22	1.058	0.0	0.0	0.0	2.248	12.937	12.676
23	1.091	0.076	0.0	0.0	2.448	11.798	11.854

TABLE D.4: Input data for a typical day in the month of April.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	6.084	4.042	3.013	0	11.304	9.941
1	11.68	0.0	0.0	0.0	0	12.15	9.535
2	10.732	0.0	0.0	0.0	0	13.058	9.15
3	11.059	0.0	0.0	0.0	0	13.821	9.921
4	11.859	4.937	2.962	2.037	0	14.485	62.939
5	11.843	5.477	2.506	2.134	0	15.122	349.274
6	10.403	5.887	3.55	2.749	0	15.798	836.169
7	10.824	6.863	3.879	3.131	0	16.585	1483.098
8	12.528	6.868	3.401	3.392	0	17.552	2176.978
9	16.849	48.73	22.8	20.563	0	18.762	985.574
10	17.618	41.667	23.771	17.211	0	19.949	1723.081
11	18.167	34.286	18.305	22.045	0	20.338	2270.352
12	15.939	30.867	17.155	20.151	0	19.559	2289.196
13	17.193	28.431	13.816	15.81	0	18.269	2174.043
14	14.136	23.133	13.689	12.262	0	17.107	2451.949
15	13.299	19.922	12.813	10.476	0	16.146	1659.602
16	11.521	19.482	11.012	9.776	0	15.331	1182.0
17	16.023	16.113	15.364	6.939	0	14.613	394.092
18	15.871	18.164	13.055	8.285	0	13.938	55.897
19	12.215	15.906	12.322	7.791	0	13.255	15.498
20	11.398	14.172	8.329	6.899	0	12.514	12.558
21	10.123	8.637	5.644	6.918	0	11.756	11.762
22	11.291	6.122	5.947	8.054	0	11.161	11.054
23	10.558	4.506	4.267	8.081	0	10.889	10.467

TABLE D.5: Input data for a typical day in the month of May.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	14.217	9.639	5.748	0	20.15	12.893
1	10.633	0.0	0.0	0.0	0	18.892	12.427
2	10.732	0.0	0.0	0.0	0	17.567	12.231
3	11.059	0.0	0.0	0.0	0	16.269	42.789
4	11.859	6.483	2.887	2.387	0	15.154	210.147
5	11.843	7.31	2.568	2.343	0	14.376	537.346
6	10.855	7.115	3.247	2.424	0	14.093	973.273
7	11.782	6.791	2.937	2.97	0	14.404	1552.92
8	10.308	8.831	3.449	2.733	0	15.201	1998.558
9	18.285	49.054	22.235	19.996	0	16.329	2267.572
10	19.194	45.886	21.896	17.925	0	17.631	2356.475
11	18.21	35.811	20.518	22.717	0	18.953	2401.041
12	12.642	41.57	16.662	20.503	0	20.206	2826.382
13	16.254	37.482	17.051	19.122	0	21.368	2574.78
14	14.812	33.517	14.192	19.409	0	22.42	2274.5
15	14.763	33.226	17.181	13.961	0	23.344	1623.836
16	15.102	38.997	17.678	15.331	0	24.121	908.779
17	16.029	29.479	24.794	13.75	0	24.684	390.765
18	14.868	30.311	20.889	13.724	0	24.89	153.577
19	12.321	31.087	17.357	12.229	0	24.648	32.326
20	11.398	32.625	17.747	11.194	0	24.057	13.631
21	10.123	20.77	10.642	13.402	0	23.25	13.701
22	11.036	15.339	10.047	14.632	0	22.295	13.602
23	10.558	10.696	8.253	13.16	0	21.223	13.236

TABLE D.6: Input data for a typical day in the month of June.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	16.962	9.439	6.43	0	22.416	13.588
1	11.68	0.0	0.0	0.0	0	21.553	14.096
2	10.732	0.0	0.0	0.0	0	20.706	67.298
3	11.059	0.0	0.0	0.0	0	19.843	243.049
4	11.859	9.017	3.58	3.019	0	18.932	566.985
5	11.843	9.106	3.621	3.037	0	17.945	1022.862
6	10.855	9.242	3.688	3.085	0	17.039	1617.867
7	11.782	9.32	3.666	3.056	0	16.617	2290.464
8	12.812	9.149	3.751	3.126	0	16.975	2805.092
9	18.036	57.325	26.646	20.282	0	17.93	3140.086
10	21.16	52.306	25.581	19.296	0	19.198	3210.079
11	19.525	46.487	19.698	23.127	0	20.618	2800.512
12	16.102	43.399	17.766	21.531	0	22.113	2471.414
13	18.251	47.659	17.061	21.373	0	23.603	1348.535
14	17.566	43.292	17.819	19.133	0	25.009	1223.35
15	18.392	40.571	18.214	16.702	0	26.236	822.97
16	17.325	43.471	20.349	15.037	0	27.182	373.054
17	16.023	40.615	24.59	14.603	0	27.745	107.253
18	15.871	39.186	22.884	14.413	0	27.824	16.882
19	12.215	35.33	22.125	14.602	0	27.387	13.287
20	11.398	34.531	18.712	14.516	0	26.563	13.335
21	10.123	21.682	13.198	13.516	0	25.503	13.403
22	11.291	16.303	12.669	15.992	0	24.359	13.39
23	10.558	11.796	9.218	15.865	0	23.276	13.491

TABLE D.7: Input data for a typical day in the month of July.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	13.847	9.015	6.756	0	22.599	13.486
1	12.949	0.0	0.0	0.0	0	21.956	13.52
2	12.349	0.0	0.0	0.0	0	21.294	13.378
3	10.333	0.0	0.0	0.0	0	20.55	13.376
4	13.378	9.085	3.428	3.0	0	19.663	24.713
5	10.877	7.722	3.211	3.302	0	18.567	132.866
6	10.173	8.415	3.314	3.499	0	17.283	138.113
7	12.462	9.216	3.323	2.606	0	16.41	540.022
8	14.044	9.229	3.918	2.814	0	16.689	801.687
9	18.5	54.492	28.705	19.106	0	17.906	1533.588
10	20.157	50.456	23.885	18.817	0	19.412	1760.573
11	17.934	44.711	21.627	22.505	0	20.939	1965.979
12	14.185	40.327	19.93	24.888	0	22.443	1699.066
13	19.273	50.639	15.587	22.026	0	23.88	2427.327
14	15.375	36.474	18.829	19.708	0	25.198	2056.554
15	17.261	33.879	17.777	18.584	0	26.312	1663.501
16	18.488	43.933	21.062	16.567	0	27.13	885.315
17	13.802	39.417	24.697	12.797	0	27.559	898.266
18	16.2	33.153	21.712	12.147	0	27.51	177.159
19	12.819	29.988	22.281	14.199	0	26.991	92.396
20	11.006	30.227	17.69	15.711	0	26.148	13.302
21	10.123	17.934	12.836	13.74	0	25.135	13.423
22	11.643	15.813	14.28	16.738	0	24.109	13.512
23	11.027	12.841	10.321	16.597	0	23.209	13.567

TABLE D.8: Input data for a typical day in the month of August.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	11.59	7.924	5.929	0	18.399	12.429
1	11.68	0.0	0.0	0.0	0	17.005	11.918
2	10.732	0.0	0.0	0.0	0	15.774	11.447
3	11.059	0.0	0.0	0.0	0	14.757	10.879
4	11.859	6.847	3.04	2.019	0	14.006	11.576
5	11.843	6.154	2.941	2.48	0	13.571	84.504
6	10.855	7.448	3.308	2.77	0	13.504	270.49
7	11.782	6.907	3.116	2.521	0	13.818	660.076
8	10.232	7.957	2.879	2.319	0	14.469	1737.15
9	13.4	39.451	19.805	15.164	0	15.41	2584.791
10	17.674	41.438	19.186	17.582	0	16.596	3186.837
11	15.727	33.759	19.304	22.415	0	17.977	3549.916
12	14.942	35.802	13.44	17.174	0	19.5	3640.917
13	17.798	38.443	15.273	17.433	0	21.04	3382.527
14	15.184	34.168	15.434	15.203	0	22.44	2966.43
15	16.036	29.645	17.672	15.33	0	23.54	2181.558
16	16.271	30.08	15.823	14.297	0	24.192	1432.46
17	14.204	35.464	22.425	14.104	0	24.432	575.109
18	12.846	32.302	22.273	12.273	0	24.44	44.19
19	12.215	25.885	17.13	12.612	0	24.24	12.307
20	11.369	30.981	18.776	13.594	0	23.67	11.497
21	10.123	15.166	10.287	11.984	0	22.663	10.56
22	11.291	11.974	12.084	15.084	0	21.35	9.935
23	10.558	9.632	7.474	13.766	0	19.879	12.77

TABLE D.9: Input data for a typical day in the month of September.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	9.011	4.773	2.988	1.997	0	8.034	8.662
1	11.68	0.0	0.0	0.0	0	9.241	8.674
2	10.732	0.0	0.0	0.0	0	11.449	8.595
3	11.059	0.0	0.0	0.0	0	13.827	8.634
4	10.471	6.415	2.89	2.6	0	15.533	9.704
5	11.94	6.648	3.49	3.031	0	16.655	22.232
6	12.51	7.944	4.082	3.3	0	17.327	31.405
7	13.177	7.1	4.192	3.568	0	17.684	89.314
8	13.639	7.578	4.529	3.048	0	17.861	204.083
9	19.644	45.678	28.449	17.649	0	17.993	442.016
10	17.733	39.987	27.146	19.975	0	18.213	609.805
11	16.885	30.994	16.144	23.105	0	18.632	798.689
12	13.608	26.529	14.978	16.334	0	19.057	589.634
13	12.821	34.557	14.215	16.991	0	19.119	533.694
14	12.053	25.56	11.555	13.74	0	18.69	407.384
15	12.616	19.691	11.151	11.577	0	17.831	514.631
16	11.457	18.425	11.166	8.922	0	16.63	122.204
17	16.023	15.304	13.286	7.723	0	15.19	9.05
18	15.871	13.963	11.346	7.674	0	13.614	8.695
19	12.215	12.208	9.728	6.545	0	12.008	8.789
20	11.398	11.883	7.83	5.348	0	10.494	8.753
21	10.123	5.834	5.207	4.877	0	9.215	8.785
22	11.291	4.441	4.818	6.251	0	8.316	8.736
23	10.558	2.864	3.552	5.498	0	7.938	8.703

TABLE D.10: Input data for a typical day in the month of October.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	0.706	0.0	0.0	4.655	6.048	8.5
1	3.061	2.962	1.369	1.068	4.485	6.133	8.852
2	3.051	1.972	1.215	1.004	4.074	6.236	8.899
3	3.058	2.062	0.873	0.727	3.176	6.442	8.788
4	3.012	1.747	0.848	0.719	2.56	6.84	9.174
5	3.031	1.577	0.838	0.617	2.738	7.514	9.145
6	11.361	8.466	4.588	3.776	2.249	8.465	48.036
7	7.89	7.721	3.478	3.263	2.523	9.576	197.356
8	13.329	9.125	5.019	4.99	2.199	10.722	981.489
9	7.623	5.716	3.62	4.04	2.705	11.777	1832.148
10	7.717	6.571	4.211	4.466	2.291	12.616	2729.217
11	6.656	5.266	3.332	5.069	0.838	13.127	3129.268
12	5.286	5.678	3.24	5.156	0.0	13.308	3134.428
13	4.614	7.424	5.293	5.088	0.0	13.187	1299.299
14	4.109	5.874	3.438	5.63	0.0	12.678	556.479
15	4.202	6.551	4.932	6.798	0.0	11.732	285.969
16	4.545	6.915	4.794	8.213	0.0	10.5	220.151
17	4.975	7.183	6.013	8.251	0.379	9.166	24.767
18	5.495	11.545	8.465	8.746	1.59	7.913	8.605
19	12.907	17.193	12.544	10.782	3.541	6.924	8.747
20	10.268	16.652	11.788	8.892	4.216	6.286	8.717
21	5.676	11.92	5.729	5.891	4.383	5.944	8.767
22	1.058	0.0	0.0	0.0	4.882	5.831	8.643
23	1.091	0.182	0.0	0.0	4.798	5.879	8.589

TABLE D.11: Input data for a typical day in the month of November.

Hour	$\dot{Q}_{d,z,1,hm}$	$\dot{Q}_{d,z,2,hm}$	$\dot{Q}_{d,z,3,hm}$	$\dot{Q}_{d,z,4,hm}$	$\dot{Q}_{d,z,5,hm}$	T_{amb}	$\dot{E}_{solar}$
0	1.297	1.116	0.0	0.0	6.022	4.436	8.504
1	3.061	4.856	1.936	1.594	7.894	3.875	8.398
2	3.051	4.077	1.986	1.394	7.372	3.425	8.512
3	3.058	4.77	2.02	1.729	5.583	3.109	8.546
4	3.012	4.056	1.796	1.477	6.73	2.953	8.681
5	3.031	4.227	1.695	1.548	5.226	2.973	8.586
6	11.361	29.18	12.543	9.742	6.731	3.164	10.662
7	7.89	24.385	9.031	10.678	6.303	3.514	32.995
8	10.119	26.198	12.547	13.402	6.272	4.01	67.199
9	7.623	17.824	9.786	11.839	6.534	4.636	157.185
10	7.717	17.265	9.19	10.24	6.42	5.381	226.086
11	6.656	14.141	6.823	9.826	2.041	6.231	276.778
12	5.286	11.587	6.793	9.102	0.0	7.173	286.055
13	4.614	12.725	7.344	9.006	0.0	8.172	272.187
14	4.109	8.554	5.826	9.015	0.0	9.097	208.854
15	4.202	7.986	5.821	7.191	0.0	9.787	202.698
16	4.545	8.138	5.857	8.56	0.0	10.085	97.466
17	4.975	7.705	6.436	9.108	0.419	9.87	18.908
18	5.495	11.77	8.556	7.939	1.25	9.235	8.721
19	10.766	18.826	11.949	9.256	3.069	8.343	8.498
20	10.745	19.283	9.571	8.519	3.132	7.359	8.662
21	5.676	13.765	4.786	5.351	4.27	6.428	8.583
22	1.058	0.0	0.0	0.0	4.356	5.595	8.45
23	1.091	0.24	0.0	0.0	5.334	4.866	8.434

TABLE D.12: Input data for a typical day in the month of December.

Appendix E

Input data for the DCS case study

The input data related to the high, medium and low load scenarios used for generating the results in the case studies are documented in the following tables.

Hour	T_{wb}	$\dot{Q}_{d,1}$	$\dot{Q}_{d,2}$	$\dot{Q}_{d,3}$	$\dot{Q}_{d,4}$
0	22.474	499.1	300.0	50.0	0.0
1	22.474	499.1	300.0	60.0	0.0
2	22.474	104.399	200.0	50.0	0.0
3	22.075	16.484	300.0	50.0	0.0
4	20.539	14.652	200.0	50.0	0.0
5	19.017	16.484	200.0	60.0	0.0
6	18.451	14.652	200.0	40.0	0.0
7	19.391	16.484	200.0	50.0	430.0
8	19.845	815.044	300.0	420.0	360.0
9	22.093	499.1	200.0	340.0	340.0
10	23.282	998.2	300.0	370.0	300.0
11	23.282	1497.3	200.0	390.0	390.0
12	23.79	1996.4	300.0	420.0	360.0
13	23.79	1497.3	300.0	430.0	370.0
14	24.225	1996.4	200.0	400.0	350.0
15	24.225	1996.4	300.0	470.0	370.0
16	23.79	1996.4	200.0	470.0	380.0
17	23.79	1996.4	300.0	420.0	370.0
18	23.79	1996.4	200.0	440.0	360.0
19	23.79	1497.3	300.0	410.0	340.0
20	23.442	1996.4	400.0	340.0	320.0
21	23.442	1996.4	200.0	90.0	20.0
22	23.442	1996.4	300.0	80.0	0.0
23	23.442	998.2	300.0	60.0	0.0

TABLE E.1: Input data for the high-load scenario.

Hour	T_{wb}	$\dot{Q}_{d,1}$	$\dot{Q}_{d,2}$	$\dot{Q}_{d,3}$	$\dot{Q}_{d,4}$
0	18.451	12.323	200.0	80.753	0.0
1	18.451	20.026	200.0	10.0	0.0
2	17.51	16.945	200.0	4.688	0.0
3	17.001	12.323	200.0	5.312	0.0
4	17.001	13.864	200.0	80.0	0.0
5	16.565	12.323	200.0	4.839	0.0
6	17.001	13.864	100.0	5.161	0.0
7	17.953	12.323	200.0	10.0	0.0
8	18.451	254.171	200.0	320.0	400.0
9	18.916	116.578	100.0	270.0	360.0
10	18.307	382.522	200.0	240.0	360.0
11	18.916	1497.3	200.0	300.0	390.0
12	17.87	1497.3	100.0	370.0	380.0
13	17.87	1497.3	200.0	380.0	390.0
14	17.804	1497.3	100.0	360.0	380.0
15	17.87	998.2	200.0	350.0	380.0
16	17.87	1497.3	100.0	330.0	380.0
17	17.953	1497.3	100.0	360.0	370.0
18	18.451	998.2	200.0	320.0	380.0
19	18.603	1497.3	100.0	270.0	370.0
20	18.603	1497.3	200.0	240.0	350.0
21	18.603	1497.3	200.0	100.0	30.0
22	18.603	998.2	200.0	6.202	0.0
23	17.51	499.1	200.0	73.798	0.0

TABLE E.2: Input data for the mid-load scenario.

Hour	T_{wb}	$\dot{Q}_{d,1}$	$\dot{Q}_{d,2}$	$\dot{Q}_{d,3}$	$\dot{Q}_{d,4}$
0	2.362	499.1	25.0	20.0	3.9
1	1.726	223.21	25.0	10.0	3.9
2	0.874	153.151	33.333	20.0	3.9
3	0.433	9.233	22.222	20.0	3.9
4	0.433	4.888	22.222	20.0	3.8
5	0.433	4.345	22.222	20.0	3.9
6	-0.224	4.345	18.182	10.0	3.9
7	-0.224	4.888	18.182	20.0	3.9
8	0.058	95.041	18.182	90.0	3.9
9	1.376	53.957	27.273	50.0	3.9
10	2.577	445.143	18.182	60.0	3.9
11	3.792	247.288	16.667	60.0	3.9
12	4.359	251.812	41.667	90.0	3.9
13	5.531	998.2	41.667	110.0	3.9
14	4.968	240.945	23.077	160.0	3.9
15	5.765	258.155	23.077	110.0	3.9
16	4.968	499.1	30.769	110.0	3.9
17	4.702	998.2	23.077	80.0	3.9
18	4.118	499.1	16.667	90.0	3.9
19	3.805	499.1	25.0	70.0	3.9
20	3.805	499.1	16.667	50.0	3.8
21	3.805	499.1	16.667	20.0	3.9
22	2.528	998.2	25.0	20.0	3.9
23	1.993	218.125	15.385	20.0	3.9

TABLE E.3: Input data for the low-load scenario.

List of Author's Publications¹

Journal Articles

- **Zhonglin Chiam**, Arvind Easwaran, David Mouquet, Samira Fazlollahi and Jaume Villa Millás, “A hierarchical framework for holistic optimization of the operations of district cooling systems,” *Applied Energy*.
- **Zhonglin Chiam**, Ilias Papas, Arvind Easwaran, Corinne Alonso and Bruno Eatibals, “Holistic optimization of the operation of a ground-sourced heat pump system: A case study on the ADREAM building in Toulouse, France,” *Energy and Buildings*, pending submission.

Conference Proceedings

- **Zhonglin Chiam**, Arvind Easwaran, David Mouquet and Mohit Gupta, “Holistic, real-time optimization of the operations of district cooling systems via deep reinforcement learning and mixed integer linear programming” in *International Conference on Applied Energy*, 2019.

¹The superscript * indicates joint first authors

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