Technical Report

Mathias Niffeler, Luis Santos,
Jordan Ivanchev, Ido Nevat

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District Cooling: What-if-Scenario Analysis

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Authors	Mathias Niffeler
Contributors	Luis Santos, Jordan Ivanchev, Ido Nevat
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Abstract

With an increase in global temperatures due to climate change, space cooling is gaining in popularity worldwide. In an attempt to provide space cooling as efficiently and with as little climate impact as possible, many cities are turning to district cooling instead of decentralised cooling solutions. However, due to the complexity of these systems, the true potential for district cooling in a given area might be hard to identify. It is thus sometimes difficult to discern whether thermal networks are implemented because they truly are the best fit for a district or simply because they are marketed as state-of-the-art.

This technical report presents a model for more informed decision-making in implementing district cooling that can systematically answer the question: WHAT is the effect on final energy demand IF current cooling systems are replaced by district cooling systems in a district by 2050? - This question is later referred to as ”*What-If-Scenario*” question.

To further broaden the view on what constitutes a good cooling system design for a district, this new model identifies systems that not only minimise energy demand but also heat emissions, greenhouse gas emissions, and cost. The model is based on a physical representation of the district's energy systems, with rule-based operation and genetic optimisation to identify the best thermal network layouts and supply system structures.

As a proof of concept, the model is applied to answer the What-If-Scenario question for Singapore's Jurong Lake District (JLD). It is shown to successfully identify 17 non-dominated cooling systems for the district despite uncertainties in parametrisation. The most cost-effective cooling system for the district consists of decentralised cooling systems in each of the buildings. The most energy-efficient system, on the other hand, includes networks that connect large portions of the community and reduce JLD's overall electricity demand by approximately 1.8 GWh per year.

This proof of concept indicates that the model can be applied to rapidly narrow down the set of sensible cooling system solutions for a district. While it doesn't provide all of the technical details required for direct implementation of the selected system, it can offer invaluable information in the concept phase of building new or retrofitting existing cooling systems for a district.

To the best of the author's knowledge, this energy system optimisation model is the first of its kind to include anthropogenic heat emissions as an objective function. In an urban context, where any heat source can potentially contribute to the urban heat island effect, this offers possibilities for future micro-climate-related studies.

CONTENTS

I. INTRODUCTION

One of the first known district cooling systems (DCS) was built in Denver, USA, in 1889 and provided refrigeration for residential homes, commercial buildings and even a meat market [1]. The Colorado Automatic Refrigeration Company, which built and operated the system at the time, had installed an ammonia-based absorption chiller system that directly supplied liquid ammonia to the connected buildings. With an evaporation temperature of -33.1°C at atmospheric pressure, ammonia was considered superior to the typical ice boxes that were prevalent then. Not only did an ammonia-based system provide up to 3 times as much cooling for the same quantity of refrigerant, but typical ice boxes would also face an issue with humidity that the closed-loop ammonia system eliminated.

While district cooling systems are not new, the technologies they use and the reasons for their deployment have shifted since the surfacing of the first systems. Østergaard et al. [2] have defined four generations of district cooling systems since their invention:

- From the late 19th century onwards, the first generation of district cooling systems was introduced primarily for refrigeration. The systems generally consisted of a centralised chiller plant and decentralised evaporators located directly in the freezers and coolers. The primary refrigerants circulating between chillers and evaporators were ammonia and brine.
- In the second generation of DCS emerging in the 1960s, the focus shifted from refrigeration to space cooling. In an attempt to profit from an economy of scale, chillers were generally one or multiple orders of magnitude bigger, and large evaporators were directly installed in the plants themselves. Chilled water was used as a medium for cold distribution.
- Around 1990, the third generation of DCS started prioritising the utilisation of local thermal energy sources like rivers, lakes, and waste heat (for absorption chillers). Large-scale 'natural' thermal storages, e.g. rock caves, were also increasingly integrated into the systems. Simultaneously, refrigerants with a high ozone depletion potential were gradually phased out.
- In the early 2000s, the fourth and most recent generation of district cooling systems started emerging. Following the smart energy system concept, these DCS were increasingly interwoven with the electrical grid and local heating systems to exploit synergies between the different energy systems.

Sustainability considerations partly drove the development of both the third and fourth-generation systems. These considerations are necessary if space cooling is not to become a significant contributor to global warming. The global energy consumption from district cooling has more than tripled since 1990, according to the International Energy Agency (IEA) [3] and will likely grow much further in the future, with only 15% of people in hot climates having air conditioners (AC) today [4].

Singapore stands out internationally, as cooling is far more prevalent. In 2017, AC ownership in residential buildings sat at around 80% [5]. WWF estimates that by 2019, the total electricity demand for cooling amounted to 15.3 TWh [6], corresponding to 29.6% of the total final electricity demand and 8.1% of the total energy demand for that year [7].

Singapore also has a relatively long history of district cooling compared to other ASEAN countries. Its first district cooling system was built by First DCS Pte Ltd and started operations in June of 2000 at the Changi Business Park. First DCS would go on to realise two more projects in Biopolis@one-north (2003) and Woodlands Wafer Fab Park (2006) before joining Keppel Group in 2009 and being renamed Keppel DHCS Pte. Ltd. [8]. Likely the company's biggest competitor to this day, Singapore District Cooling by SP Group, joined the market in 2006 with the successful launch of their lighthouse project at Marina Bay [9]. While only one more project has commenced operations since then - a district cooling system at Mediapolis@one-north built by Keppel DHCS in 2015 - at least five more projects are currently in planning, namely at Tengah, Ang Mo Kio, Punggol, Tampines and the new Jurong Innovation District.

All existing district cooling systems in Singapore would likely fall into the definition of a 2nd generation district cooling system. Therefore, the primary perk of district cooling they benefit from is the economy of scale effect. As climate change increasingly impacts our planet and our urban environments, other benefits of district cooling systems might increase in value. Using the interconnectivity of energy systems, a typical feature of 4th generation systems, could open up possibilities for intermittent energy storage, further increasing energy efficiency. And utilising local thermal energy sinks such as rivers, lakes, or the sea (a key characteristic of 3rd generation systems) can help redirect waste heat from cooling systems away from the most densely populated urban areas.

The anthropogenic heat emitted from building cooling systems has been studied in a previous phase of the Cooling Singapore project [10], and its contribution to the urban heat island (UHI) effect has been modelled to temporarily be as high as 2°C and approximately 0.8°C on average [11]. Modelling of district cooling has shown that these systems can successfully shift the anthropogenic heat, increasing peaks of the UHI effect locally but reducing it on average [12].

I-A. Objectives

This report presents a model that enables a fast preliminary analysis of the potential of district cooling in a given district in terms of reducing cost, energy demand, and anthropogenic heat emissions. As a test case, this model will address the following What-if-Scenario (WiS) question, as it was outlined in the WiS Description of 17 February 2022:

> **WHAT** is the effect on final energy demand
> **IF** current cooling systems are replaced by district cooling systems
> **IN** a district
> **BY** 2050

As defined in the WiS description, the final energy demand refers to the combined energy content [in GWh] of all energy carriers used to operate the cooling system for one year. The sample district chosen for this study is the Jurong Lake District (JLD), which will house the new Jurong Innovation District in the future.

II. Methodology

II-A. Description of the domain / Model parametrisation

The model presented in this report introduces the definition of a *domain* as a formal description of the district(s) for which the potential for district cooling shall be determined. The variables representing a domain can be split into two subsets, i.e.:

- Local variables that change with the selection of the domain boundaries
- Global variables that remain constant, independent of the domain selected (as long as the domain is situated in the same geographical region).

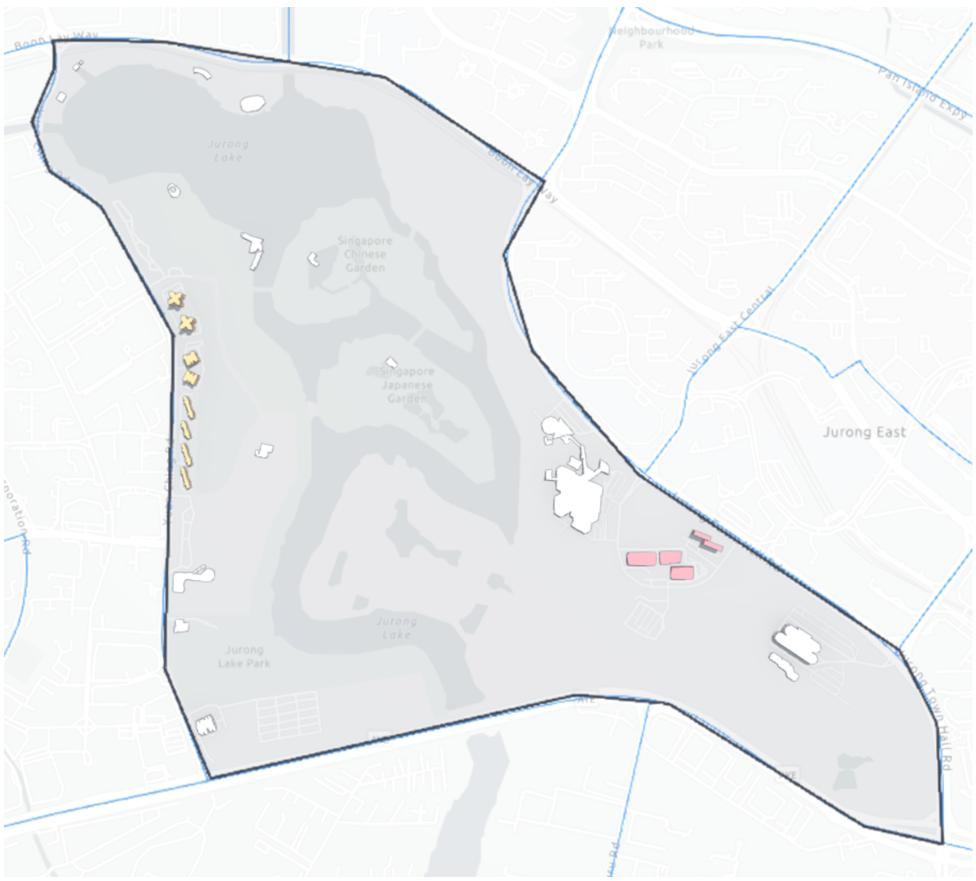

Fig. 1: *Typical domain used for analysing district cooling system potentials.*

1 Local parameters

Every domain is defined by a set of location-specific parameters. As the name implies, these *local parameters* are dictated by the domain's exact geographical location within a given region, i.e.

Singapore, in the case of this study.

1) The characteristic timeframe $\mathcal{T}$ of T consecutive time steps, i.e. $\mathcal{T} := \{1, ..., T\}$, that allow for a complete description of the typical behaviour of the district(s).
2) The set of buildings $\mathcal{B} := \{1, ..., B\}$ within the domain, which are characterised by:
   - their cooling demand $\{D_i\,(t)\}_{i=1}^{B}$ for each time step t and $t \in \mathcal{T}$?
   - the centroids of their footprints $\mathcal{F} := \{\mathtt{v}_i = (\vartheta_i, \varphi_i)\}_{i=1}^{B}$ in two dimensional Cartesian space.
3) The *potential networks graph* $G_N = (\mathcal{V}, \mathcal{L})$ representing paths along which the pipes for the district cooling network can be placed. The potential networks graph consists of the following:
   - V vertices $\mathcal{V} := \{\mathtt{v}_i = (\vartheta_i, \varphi_i)\}_{i=1}^{V}$ with $\mathcal{F} \subseteq \mathcal{V}$ and
   - L links between pairs of vertices $\mathcal{L} \subseteq \{(\mathtt{v}_i, \mathtt{v}_j) \,|\, (\mathtt{v}_i, \mathtt{v}_j) \in \mathcal{V} \text{ and } i \neq j\}$.

2 Global parameters

Apart from local parameters, there is also a set of parameters that are independent of the exact location of the domain and are valid for all domains within a broader region, i.e. all of Singapore in the case of this study. These parameters are categorised as *global parameters* here.

Technology Specifications

The first set of these global parameters describes the state of technology, more explicitly, the two integral parts of the district cooling systems, i.e. the thermal network and the cooling plant. They are characterised by the available technologies for *network piping* and *cooling components*, respectively.

The network piping is assumed to consist of steel pipes encased in an insulation layer of calcium silicate. Therefore, the remaining relevant parameters to describe the available pipe types $P \in \mathcal{P}$ are the following:

- The pipe's dimensions, i.e., the internal radius r_P, the external radius R_P of the steel pipes, and the thickness d_P of their thermal insulation.
- The cost per unit length c_P of each pipe type.

The cooling components are more complex to describe since they are machines with varying operating mechanisms (e.g. heat exchangers, chillers, cooling towers). However, the parameters that are common to every type of component type $O \in \mathcal{O}$ can be summarised as follows:

- The range of component sizes available on the market, spanning from a minimum capacity $C_{min,O}$ to a maximum capacity $C_{max,O}$.

- The efficiency function $\varepsilon_O(P, C)$, that depends on the power output P and the capacity C of an installed component.
- The cost function $c_O(C)$, that depends of the capacity C of the installed component.

Energy Carriers

The second set of global parameters $\mathcal{K}$ describes the available energy carriers in the broader geographical region. This description includes:

- A unique categorisation of the *energy carrier* k consisting of a type descriptor $\mathtt{T}_k$ and a quality descriptor $\mathtt{Q}_k$ (an example of this is shown in table III).
- The greenhouse gas emissions intensity of the energy carrier $\mathtt{e}_k$.
- The unit cost of the energy carrier $\mathtt{c}_k$

ENERGY CARRIER	**chilled water**	**low voltage electricity**	**coal**
type descriptor $\mathtt{T}_k$	thermal EC - water	electricity - AC	combustible EC - fossil fuel
quality descriptor $\mathtt{Q}_k$	10°C	230V	anthracite

TABLE I: *Examples of energy carrier categorisations.*

Weather

While solar radiation, humidity, and air temperature all play a role in the final cooling demand of buildings, only the outdoor air temperature $\Theta(t)$ for each timestep $t \in \mathcal{T}$ is considered necessary in determining the performance of district cooling systems. This is due to the temperature influencing the performance of certain cooling system components like cooling towers and the losses in the network pipes.

II-B. Description of Cooling Systems / Model description

The parametrisation of the domain constitutes the basis for exploring the impact of specific *District Cooling Systems* (DCS). The simplified approach taken in this model concentrates on two main variables for describing these potential DCS: Connectivity and Cooling Plant Capacities. These two variables, along with a set of physical laws and engineering principles, dictate system installation and operation and, therefore allow for an evaluation of any DCS design.

1 Connectivity

Connectivity describes which buildings are connected by the same network of pipes and, therefore belong to the same district cooling system. These network connections shall be defined as follows:

- There are N district cooling *networks* in the domain that a building can be serviced by.
- Let x_i denote the *connectivity state* of the i-th building, where $x_i \in \mathcal{X}$, and $\mathcal{X} := \mathcal{N} \cup \{0\}$, and $\mathcal{N} := \{1, \ldots, N\}$:

$$x_i = \begin{cases} 0, & \text{the i-th building is not connected to any network.} \\ n \in \mathcal{N}, & \text{the i-th building is connected to the n-th network.} \end{cases} \tag{1}$$

- The collection of all buildings' connectivity states is given by the *connectivty vector:*

$$\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_B \end{bmatrix} \in \mathcal{X}^B \tag{2}$$

Connectivity state x	0	2	0	0	1	2	2	2	0	1	0	0	0
Building b	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*

TABLE II: *Example of a connectivity vector* $\mathbf{x}$ *for a domain with thirteen buildings and two district cooling networks.*

2 Cooling Plant Capacity

Every network's power plant needs to provide enough cooling to supply all buildings connected to it. However, there is a multitude of combinations of different cooling components that can result in the same overall plant capacity. Some of them are more efficient, cheaper or less emission-intensive than others. Therefore, the following definition aims to quantify the share of the required energy each viable component of a district cooling plant can provide in a given plant design so that the various options can be evaluated and compared adequately.

- Let each component $j \in \mathcal{O}$ have exactly one main (input or output) energy carrier $k \in \mathcal{K}$ and let this relation be described by the mapping function $\xi : \mathcal{O} \to \mathcal{K}$.
- Let the n-th *capacity indicator vector* $\mathbf{y}_n$, with $\mathbf{y}_n \in \mathcal{Y}, \mathcal{Y} = [0 \;\; 1]^{|\mathcal{O}|}$, indicate the fraction (between 0 and 1) of the *maximum demand* (see II-B3) for each component's respective main energy carrier, $k = \xi(j)$, that each component $j \in \mathcal{O}$ of the n-th district cooling plant can convert/produce under peak operating conditions.
- The collection of all N district cooling plant's capacity indicator vectors is given by the *capacity indicator matrix*:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_N \end{bmatrix} \in \mathcal{Y}^N \tag{3}$$

	absorption chiller	*vapour compression chiller*	*gas boiler*	*oil boiler*	*generator*	*cooling tower*
network 1	0.8	0.7	0.7	0.2	0.5	1
network 2	1	0	0.8	0.3	0	1

TABLE III: *Example of a capacity indicator matrix for a domain with two networks and six possible cooling system components.*

3 System Installation

While the connectivity vector and capacity indicator matrix are the model's only variables, they don't define all details of the respective DCS's installation and operation. The following rules and principles are introduced to complete the description of exactly how district cooling systems should be built.

1) Given the domains' connectivity vector $\mathbf{x}$, the buildings connected to the same district cooling network $\mathcal{B}_n \subseteq \mathcal{B}$ are linked by determining the minimum spanning tree G_n connecting the building centroids $\mathcal{F}_n := \{\mathrm{v}_i = (\vartheta_i, \varphi_i)\}, i \in \mathcal{B}_n$ through the potential networks graph G_N (approach by Melhorn [13]).
2) The demand profile of all connected buildings and the thermal losses L_l across the network's

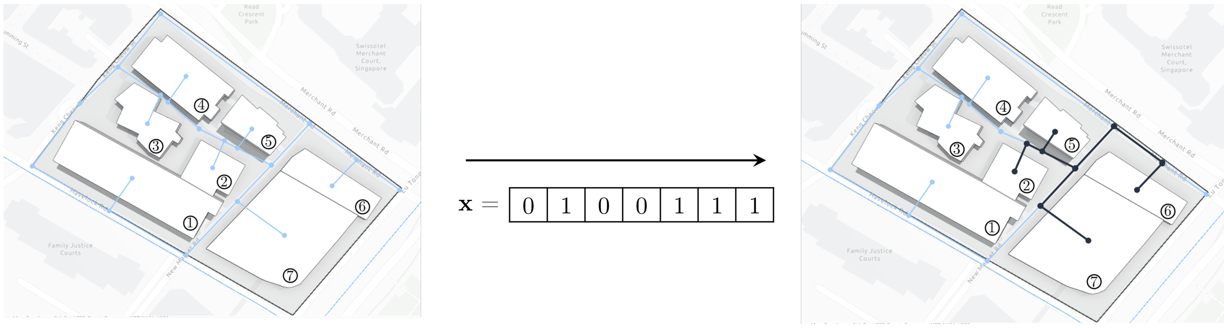

Fig. 2: *Example of how a network is built based on a given connectivity vector* $\mathbf{x}$.

links l are aggregated to calculate the network n's thermal energy demand:

$$D_n(t) = \sum_{i \in \mathcal{B}_n} D_i(t) + \sum_{l \in G_n} L_l(t) \tag{4}$$

3) The capacities of the primary components $\mathcal{O}_P \subset \mathcal{O}$ (i.e. main cooling components) is determined by multiplying the *maximum network cooling demand* M_n of the n-th network by the capacity indicators $\mathbf{y}_n$:

$$M_n = \max_{t \in \{1,\ldots,T\}} D_n(t) \tag{5}$$

$$\{C_{n,j} := y_{n,j} * M_n\}_{j \in \mathcal{O}_P} \tag{6}$$

$\mathcal{O}_P \subset \mathcal{O}$ contains all components j whose main energy carrier matches $\xi(j)$ the energy carrier required by the network (e.g. 'chilled water').

4) The maximum energy inputs for any energy carrier k required by the primary components $j \in \mathcal{O}_P$ are calculated using their respective energy carrier specific efficiency functions $\varepsilon_j(P, C, k)$:

$$M_S(k) = \sum_{j \in \mathcal{O}_P} \left(\varepsilon_j(C_{n,j}, C_{n,j}, k) * C_{n,j}\right) \tag{7}$$

The secondary component $\mathcal{O}_S$ (i.e. supply components) are sized by taking these primary component inputs as their *maximum demand* requirement. Their capacities are therefore calculated as follows:

$$\{C_{n,j} := y_{n,j} * M_S(k)\}_{j \in \mathcal{O}_{S,k}} \tag{8}$$

$\mathcal{O}_{S,k} \subseteq \mathcal{O}_S \subset \mathcal{O}$ denotes all available cooling system components j that produce the energy carrier k (e.g. low voltage electricity) as their main output $\xi(j)$.

5) Lastly, capacities of the tertiary components $\mathcal{O}_T$ (i.e. heat rejection components) are calculated similarly, but this time, based on the maximum outputs $M_T(k)$ of an unused/waste output energy carrier k of primary and secondary components:

$$M_T(k) = \sum_{j \in \mathcal{O}_P \cup \mathcal{O}_S} \left(\varepsilon_j^* \left(C_{n,j}, C_{n,j}, k \right) * C_{n,j} \right) \tag{9}$$

$$\left\{ C_{n,j} := y_{n,j} * M_T(k) \right\}_{j \in \mathcal{O}_{T,k}} \tag{10}$$

$\varepsilon_j^*(P, C, k)$ denotes the waste energy ratio, establishing the relation between the output of energy carrier k and the component j's main output of energy carrier $\xi(j)$. $\mathcal{O}_{T,k} \subseteq \mathcal{O}_T \subset \mathcal{O}$ denotes all components that are primarily used to absorb/convert/reject energy carrier k (e.g. cold water).

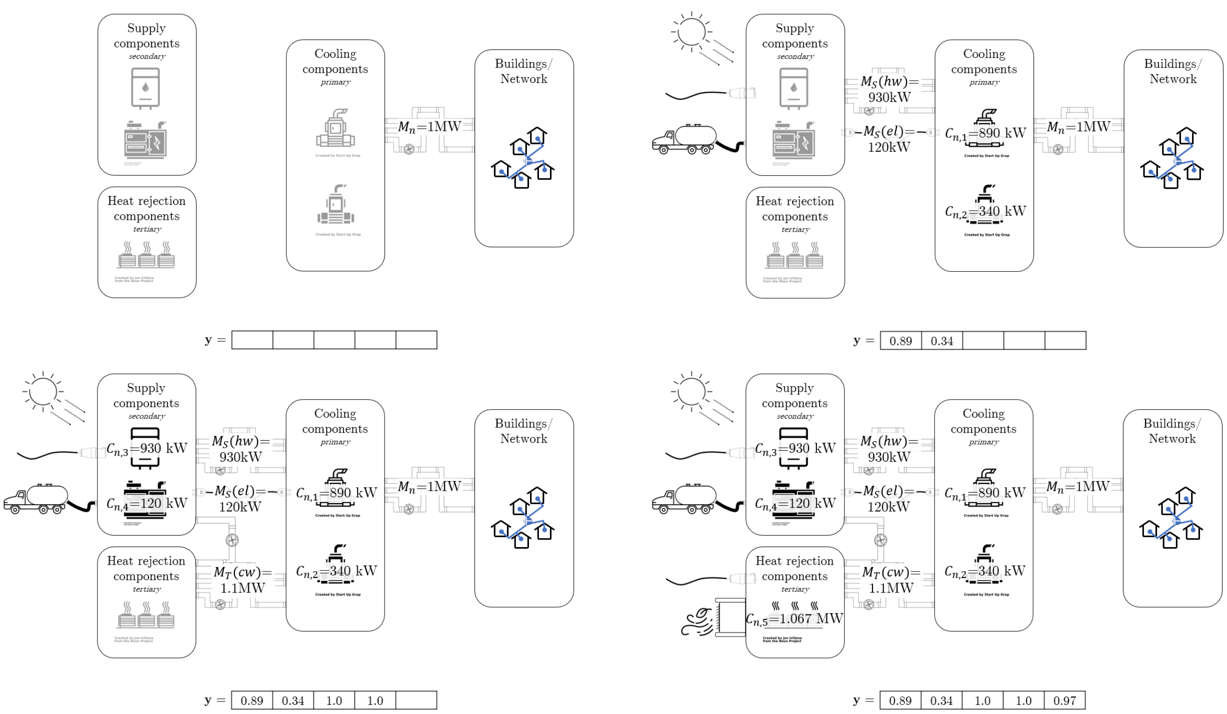

Fig. 3: *Example of how a supply system is built based on a given capacity indicator vector* $\mathbf{y}$ *for a network.*

4 System Operation

The main principle governing the operation of a district cooling supply system in this model is the 'water-filling' or cascading principle. This principle shall be defined as follows:

For a given supply system of a network n, the activation chain of components j of the same class $\mathcal{O}_X$ (i.e. primary, secondary or tertiary), that share the same main energy carrier k, is given by a predefined activation order of the components $\mathsf{A}_{X,k}; X \in \{P, S, T\}$ (ordered set of component identifiers).

The power $P_{n,j}(k)$ allocated to the components to meet the combined main power input or output, denoted by $\hat{P}_n(k)$, is expressed via the mapping $\mathbf{w}$ as follows:

$$\{P_{n,j}(k)\}_{j\in \mathsf{A}_{Xk}} = \mathbf{w}\left(\{C_{n,j}\}_{j\in \mathsf{A}_{Xk}}, \hat{P}_n(k)\right), \tag{11}$$

with

$$P_{n,A_{Xk}(m)}(k) = \begin{cases} C_{n,A_{Xk}(m)}, & \forall m \in \{1,\dots,w_n^*-1\} \\ \hat{P}_n(k) - \sum_{l=1}^{\omega^*-1} C_{n,A_{Xk}(m)}, & m = w_n^* \\ 0, & \forall m > w_n^*+1 \end{cases} \tag{12}$$

where

$$\begin{aligned} w_n^* :=& \min_{w\in\{1,\dots,|\mathsf{A}_{Xk}|\}} w \\ s.t.& \sum_{l=1}^{\omega} C_{n,A_{Xk}(l)} - \hat{P}_n(k) \geq 0. \end{aligned} \tag{13}$$

II-C. Optimisation

With domain parameters, system installation, and operation principles set, the search for a domain's optimal district cooling system can begin. In the context of this model, the optimal district cooling systems for a domain are those that minimize cost, system energy demand, greenhouse gas emissions, and anthropogenic heat release.

$$\begin{aligned} (\mathbf{x}^*, \mathbf{Y}^*) = \underset{\mathbf{x}\in\mathcal{X}, \mathbf{Y}\in\mathcal{Y}}{\arg\min} \left[f_c\left(\mathbf{x}, \mathbf{Y}\right), f_e\left(\mathbf{x}, \mathbf{Y}\right), f_g\left(\mathbf{x}, \mathbf{Y}\right), f_h\left(\mathbf{x}, \mathbf{Y}\right)\right] \\ \text{s.t. cooling demand is met.} \end{aligned} \tag{14}$$

$f_c\left(\mathbf{x}, \mathbf{Y}\right)$: annual investment and operational cost of the domain's cooling system
$f_e\left(\mathbf{x}, \mathbf{Y}\right)$: total annual energy inputs for operating the domain's cooling system
$f_g\left(\mathbf{x}, \mathbf{Y}\right)$: total annual greenhouse gas emissions from the operation of the domain's cooling system
$f_h\left(\mathbf{x}, \mathbf{Y}\right)$: total annual heat emissions of the domain's cooling system

The genetic optimisation algorithm presented in Algorithm 1 was selected to solve this problem.

Genetic algorithms mimic the process of natural selection to solve complex problems by representing potential solutions as vectors of values akin to genomes in living organisms. Through an iterative process, these vectors undergo mutation and recombination, resulting in a mix of new potential solutions. Each iteration involves evaluating these solutions, retaining the best-performing ones, and discarding the less promising ones.

While genetic algorithms do not guarantee finding the best solution, they offer an efficient approach for identifying near-optimal solutions to an optimisation problem. Most importantly, genetic algorithms can be applied to nearly all types of optimisation problems. Therefore, they are often an invaluable backup option for non-linear, multi-objective problems with non-convex solution spaces - such as the problem presented in equation 14 - where simpler and faster-solving algorithms cannot be applied.

Algorithm 1 Encased genetic algorithm

Input: population size $\mathtt{P}$, number of generations $\mathtt{G}$

Output: The optimal network and supply system layout for district cooling in a given domain

Generate population of $\mathtt{P}$ possible connectivity vectors $\{\mathbf{x}_i\}_{i=1}^{\mathtt{P}}$

for $g_1 \leftarrow [1, \mathtt{G}]$ **do**

  if $g_1 \geq 2$ **then**

    mutate and recombine $\{\mathbf{x}_i\}_{i=1}^{\mathtt{P}}$ to create child population $\{\mathbf{x}_i^*\}_{i=1}^{\mathtt{P}}$

  else

    $\{\mathbf{x}_i^*\}_{i=1}^{\mathtt{P}} = \{\mathbf{x}_i\}_{i=1}^{\mathtt{P}}$

  Determine networks $\{G_n\}$ using the minimum spanning tree

  Generate population of $\mathtt{P}$ possible capacity indicator matrices $\{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$ for each $\mathbf{x}_i^*$

  for $g_2 \leftarrow [1, \mathtt{G}]$ **do**

    if $g_2 \geq 2$ **then**

      mutate and recombine $\{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$ to create child population $\left\{\mathbf{Y}_{i,j}^*\right\}_{j=1}^{\mathtt{P}}$

    else

      $\left\{\mathbf{Y}_{i,j}^*\right\}_{j=1}^{\mathtt{P}} = \{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$

    Evaluate f_c, f_e, f_g, and f_h for all $\left(\mathbf{x}_i, \mathbf{Y}_{i,j}^*\right)$

    Combine $\{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$ and $\left\{\mathbf{Y}_{i,j}^*\right\}_{j=1}^{\mathtt{P}}$ in the objective-function space and identify non-dominated fronts [14]

    Select $\mathtt{P}$ least dominated $\mathbf{Y}$-solutions for each $\mathbf{x}_i^*$ and replace $\{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$;

  if $g_1 = 1$ **then**

    $\left\{\mathbf{Y}'_{i,j}\right\}_{j=1}^{\mathtt{P}} = \{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$

  Combine $\left\{\left\{\left(\mathbf{x}_i, \mathbf{Y}'_{i,j}\right)\right\}_{j=1}^{\mathtt{P}}\right\}_{i=1}^{\mathtt{P}}$ and $\left\{\{(\mathbf{x}_i^*, \mathbf{Y}_{i,j})\}_{j=1}^{\mathtt{P}}\right\}_{i=1}^{\mathtt{P}}$ in the objective function space and identify non-dominated fronts [14]

  Select $\mathtt{P}$ least dominated $\mathbf{x}$-solutions and replace $\{\mathbf{x}_i\}_{i=1}^{\mathtt{P}}$;

  $\left\{\mathbf{Y}'_{i,j}\right\}_{j=1}^{\mathtt{P}} = \{\mathbf{Y}_{i,j}\}_{j=1}^{\mathtt{P}}$

return $\left\{\{(\mathbf{x}_i, \mathbf{Y}_{i,j})\}_{j=1}^{\mathtt{P}}\right\}_{i=1}^{\mathtt{P}}$

III. JLD CASE STUDY

III-A. Simulation Scenario

As a proof of concept for this model, the potential for district cooling was analysed in the Jurong Lake District (JLD). JLD lies in the western part of Singapore and, as its name implies, is home to Jurong Lake, a 70-ha freshwater lake and reservoir surrounded by a park. As could be expected, JLD's population density is lower than the national average, making it potentially less suitable for district cooling.

But to definitively answer that question and determine the energy reduction potential of district cooling as proposed in section I-A, the optimisation model presented in II was run for JLD. The identified district cooling system solutions were compared to the current cooling system in JLD (base case). In the base case, buildings in JLD were assumed to each have their own central cooling systems. As explained in the next section, III-B, this might not perfectly reflect reality but corresponds to the best possible approximation given available datasets.

In fact, the experimental setup described in III-B could be adapted to any other district to replicate this proof of concept elsewhere.

III-B. Experimental Setup

The majority of parameters describing JLD were either taken directly from open-source databases or approximated based on publically available documents. Some other parameters, especially those defining spatial or temporal boundaries, inherently involve an element of user selection. These parameters were generally freely chosen by the authors of this report to reflect the WiS-question defined in I-A.

The local parameters (see II-A1) were chosen as follows:

- The characteristic timeframe $\mathcal{T}$ for the simulation of the district's cooling systems was chosen to be one year divided into 1-hour time steps.
- A total of $B = 31$ buildings with cooling systems were identified in JLD based on Open Street Maps (OSM) information. Demand profiles were approximated based on building size and use types using the City Energy Analyst (CEA) software. The total cooling demand calculated for all buildings in the district amounts to approximately 68 GWh per year.
- OSM's road and path segments were taken for the district's potential networks graph G_N.

The global parameters (see II-A2) were set as follows:

- The CEA software offers technology specifications for many cooling system components in their default databases. While their sources are not always declared, these databases were used in this analysis as more reliable information was unavailable.
- Cost and GHG-emission intensity of available energy carriers were also taken from the CEA databases. However, these parameters are more clearly traceable than the component and pipe specifications.
- The typical hourly outdoor air temperature profile $\Theta(T)$ used for the analysis is based on measurements for Singapore's Changi airport between 1990 and 2010.

The district cooling model presented in II was run for a maximum of $N = 2$ district cooling networks to be installed in JLD. Any building in the district is allowed to be connected to any of the two networks.

A set $\mathcal{O}$ of 17 different viable cooling system components were proposed for selection, i.e.:

- 2 types of direct exchange air conditioners
- 2 vapour compression chiller models
- 3 absorption chiller models
- 2 types of cooling towers
- 3 heat pump models
- 3 types of boilers
- 2 types of cogeneration devices

As for the parameters of the genetic algorithm, the population size was set to $P = 10$, netting a total of $10 * 10 = 100$ different system compositions investigated per generation, for a total of $G = 10$ generations.

The objective functions for this analysis of JLD were reduced from four to three, i.e. heat emissions, system energy demand and cost, in line with preferences expressed by the Singaporean agencies involved in this project.

III-C. Results

The results presented in this chapter investigate potential district energy systems for Singapore's Jurong Lake District (JLD). Like any problem with multiple objectives, many district cooling systems can be considered optimal when simultaneously analysed for system energy demand, anthropogenic heat emissions and cost. For example, while one system might come with the lowest cost, it might consume more energy than another.

In fact, any solution of a multi-objective optimisation problem that can not be improved in terms of one objective without worsening another is called a non-dominated or Pareto-optimal solution - after Vincento Pareto, who first described this trade-off while studying resource allocation and social welfare [15].

For simplicity's sake, the results presented here are reduced to a general analysis of the solution space of Pareto-optimal district energy systems for JLD and a subsequent in-depth analysis of three of the solutions. The latter analysis could be extended to other non-dominated solutions depending on the model's user's interests.

1 Solution Space

Running the optimisation algorithm described in II-C with the parameters from III-B resulted in 17 non-dominated district cooling system designs for JLD. Each of these solutions is characterised by a combination of system energy demand, anthropogenic heat emissions and system cost that trumps all other systems tested by the algorithm.

Figure 4 shows the non-dominated building systems in the three-dimensional space prescribed by the problem's objective functions. The solutions span from an annual system energy demand of 11.5 GWh to 13 GWh yearly. This corresponds to between 0.078% and 0.089% of the annual energy demand for cooling in Singapore [7] and yields a seasonal coefficient of performance (SCOP) of between 5.2 and 5.9 for the cooling systems.

The non-dominated district energy systems cost between 6.4 and 6.8 million USD annually, i.e. 8.7 - 9.3 million SGD annually. This would result in a price between 9.4 - 10 cents USD per kWh (12.8 - 13.6 cents SGD per kWh) of cooling delivered.

The heat emissions for the optimal cooling system solutions range from 76 GWh per year to 82 GWh per year. This corresponds to the heat of combustion in approximately 5000 - 7000 tonnes of natural

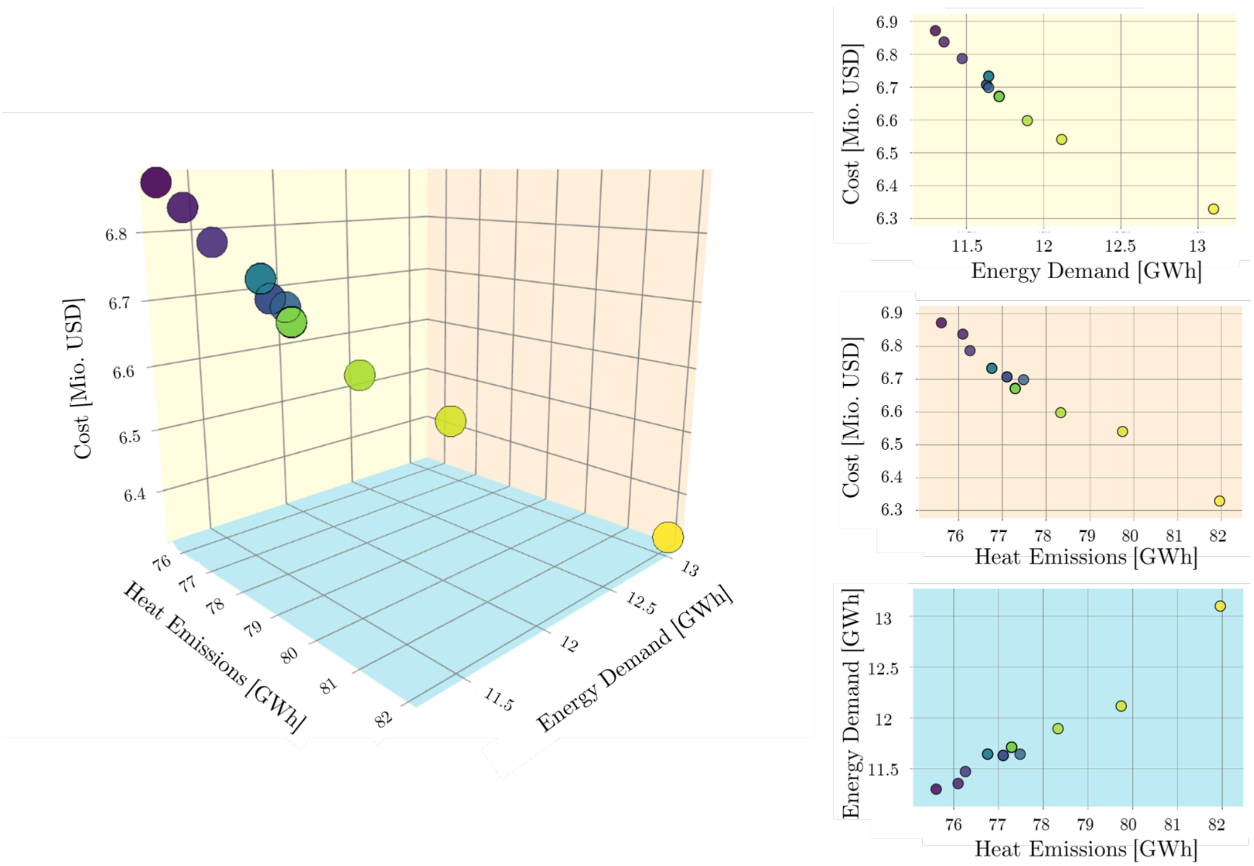

Fig. 4: *3D Pareto-front of district cooling system solutions identified for JLD (left) and projections to the corresponding 2D spaces described by pairs of two out of the three objective functions (right).*

gas, i.e. 0.06% - 0.083% of Singapore's annual natural gas imports [7].

One trait of the Pareto-optimal solutions space of this problem that is instantly apparent is the positive correlation between system energy demand and heat emissions. Typical multi-dimensional Pareto-fronts for minimisation problems, in contrast, would reduce the value of one objective while increasing the value of the other, i.e. display a negative correlation.

2 Focus on Specific Solutions

We shall focus on three of the 17 optimal cooling system designs to illustrate the details of the supply systems the algorithm identifies - first, the two extremes, minimising cost and heat emissions/system energy demand, respectively. And since the lowest-cost solution does not introduce any district cooling networks in JLD, we will also focus on the second-lowest-cost solution.

S1: **lowest cost** - As mentioned, this solution does not introduce new district cooling systems into JLD. This means that buildings simply operating their current, decentralised cooling systems and replacing them at the end of their lifetime would lower costs more than introducing any district cooling system investigated when running the algorithm.

S2: **lowest heat emissions and system energy demand** - The cooling system solution minimising energy demand and heat emissions introduces two district cooling systems in JLD. Their networks span from one end of the district to the other and are depicted in figure 5. The first network's cooling plant is located at the Science Center Singapore, and the other is at Jurong Town Hall. Figures 8 and 9 in appendix A provide depictions of the supply systems that would need to be installed in the plants of these district cooling networks to reach minimal heat emissions and system energy demand.

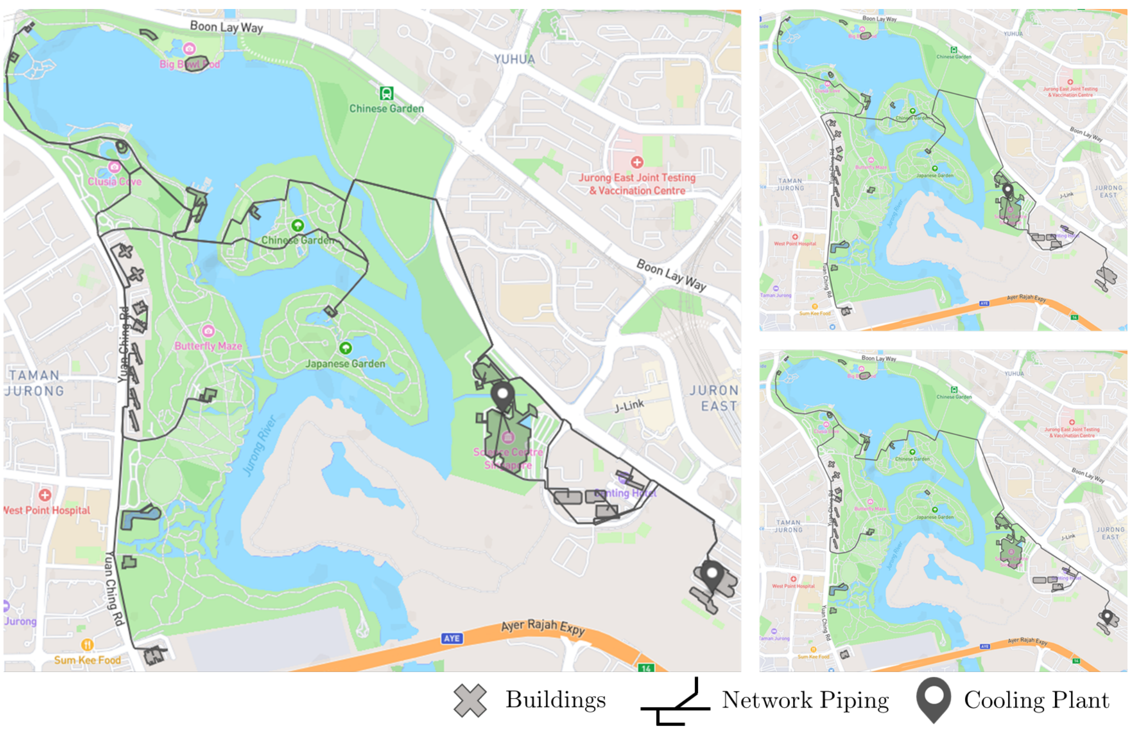

Fig. 5: *S2 - Solution with lowest heat emissions and system energy demand, with two district cooling networks, both spanning from the east to the west side of Jurong Lake.*

S3: **second-lowest cost** - The second-lowest-cost solution introduced two relatively compact district cooling systems. One is on the east side and the other on the west side of Jurong Lake, as shown in figure 6. The optimal supply systems identified for each of these networks are displayed in figures 10 and 11 in appendix A. Both are electrically driven, with water-source vapour compression chillers (VCC) providing cooling and cooling towers (CT) evacuating the system's heat.

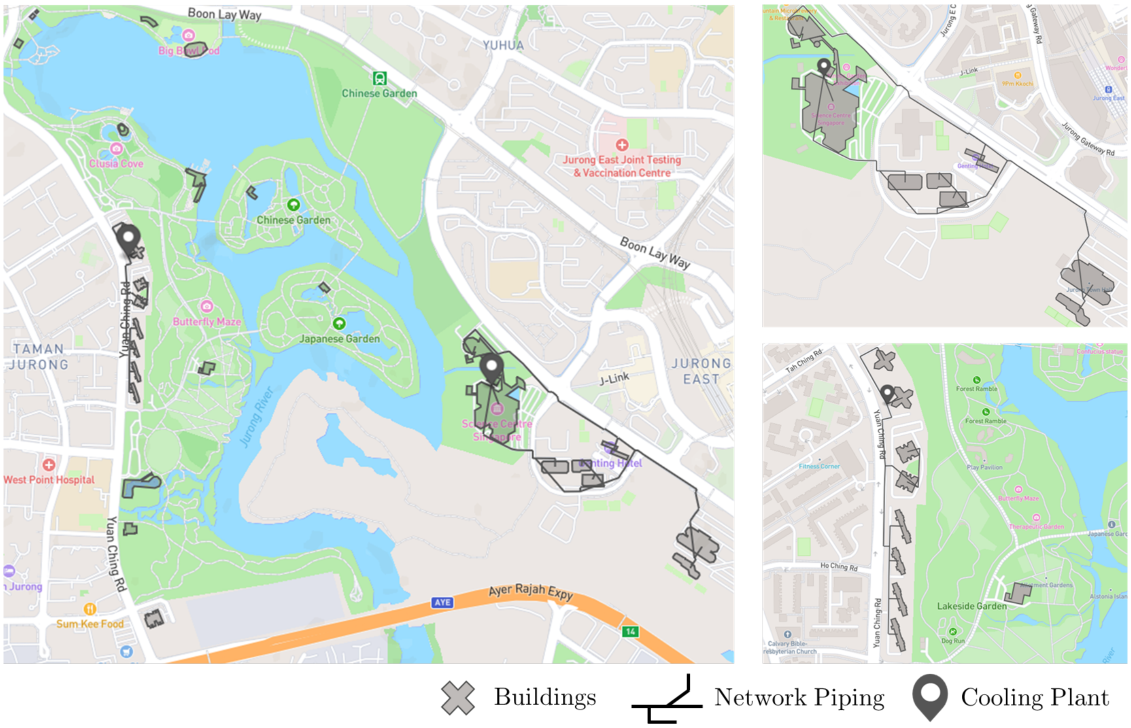

Fig. 6: *S3 - Solution with second-lowest cost, consisting of two small district cooling systems in the east and west of Jurong Lake.*

III-D. Discussion

As described in I-A, the main purpose of the optimisation model presented in this report is to identify the potential of district cooling in a given district. But before further analysing the results, it is essential to establish the context in which they were generated.

1 Convergence

Interpreting the cooling system results presented in III-C as near-optimal solutions is valid only if the algorithm can reasonably be assumed to have converged close to the actual Pareto-front. For complex systems such as district energy systems, the true Pareto-front is very hard to determine, but convergence (at least to a local optimum) can be assumed when there is little to no change in the non-dominated front over multiple generations of tested solutions.

The evolution of the non-dominated front of cooling system solutions is displayed in figure 7. As expected, the solutions gradually show lower system energy demand, heat emissions and cost. Additionally, the non-dominated fronts for generations 7, 8 and 9 largely overlap, which indicates that further improved cooling systems become harder to identify, and the solutions are thus likely approaching Pareto-optimality.

The mutation and crossover operations to find these non-dominated fronts were mainly automated. However, some new network connectivity mutations were introduced manually at generation 8 of the evolutionary algorithm. In fact, the network connectivity states of the two lowest-cost solutions of the algorithm were part of these manually introduced mutations.

2 District Cooling Potential in JLD

The optimisation results generated for JLD suggest that the current cooling system, where each building has its own cooling supply, is the most or at least one of the most cost-effective cooling systems for the district. However, thermally interconnecting the district's buildings could reduce energy demand and heat emissions. Introducing district cooling networks in JLD could reduce system energy demand by as much as 14% (i.e. 1.8 GWh per year) and heat emissions by up to 9% (i.e. 6.5 GWh per year) at an annual extra cost of 550'000 USD (i.e. 750'000 SGD per year).

Like the current building's individual cooling systems, the optimal networks' supply systems rely primarily on electricity for cooling. These supply systems typically consist of vapour compression chillers and cooling towers. As such, the identified solutions primarily rely on an economy of scale effect for their increased efficiency (typical of 2nd generation district cooling systems).

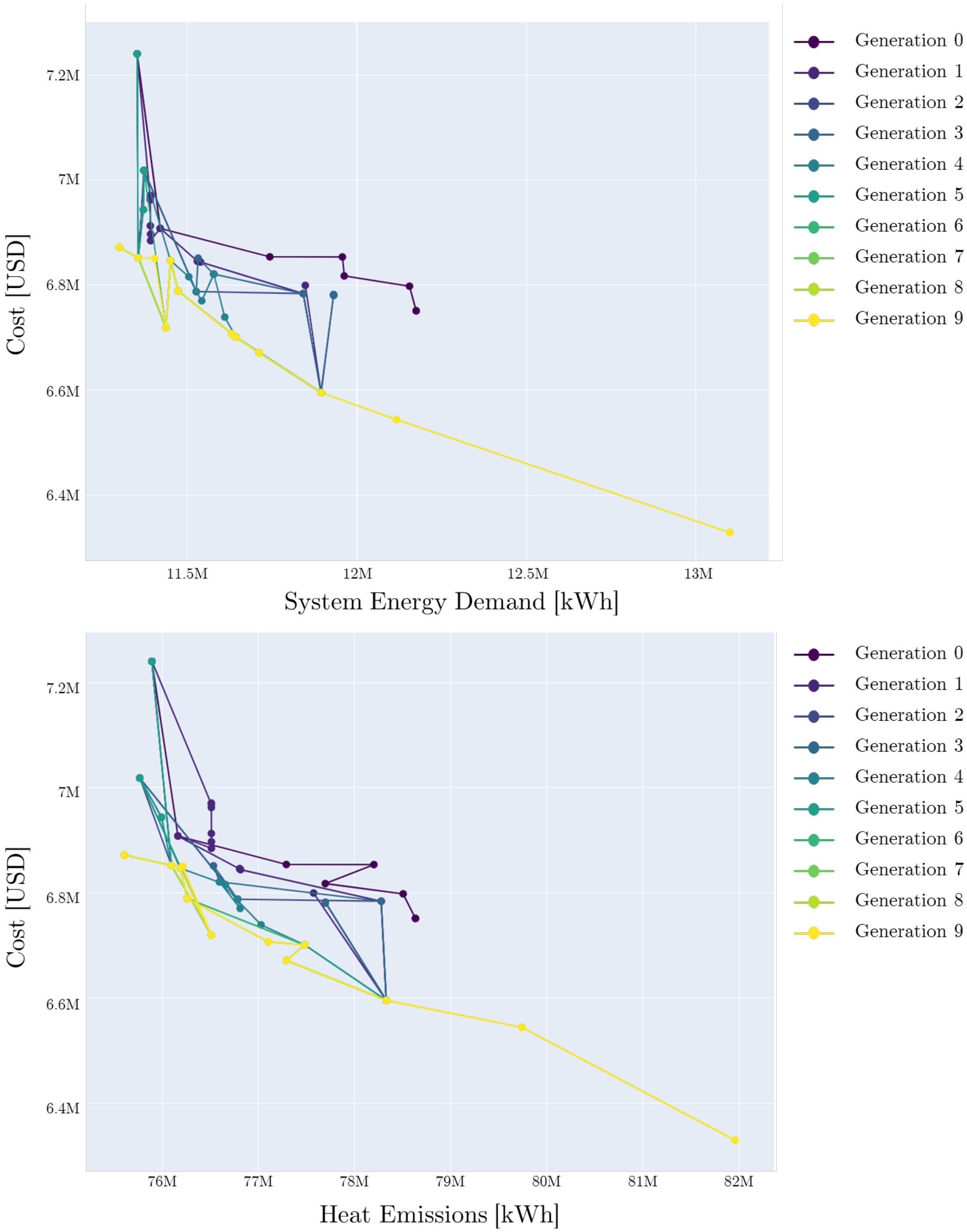

Fig. 7: *Evolution of non-dominated front of cooling system solutions across ten generations of network connectivity vectors.*

The system efficiency could likely be improved further with the utilisation of renewable energy potentials, given the district's large water body and surface area. However, renewable energy potentials were not analysed in the scope of this optimisation.

IV. CONCLUSION

The results of the cooling system optimisation of Jurong Lake district show some promise for the model described in II but also unmask two shortcomings of the current model and its parametrisation. This last section will thus focus on what can be gained from correcting the current flaws and what can already reliably be extracted from the current model's results.

IV-A. Model Limitations

The first shortcoming of the presented model is uncovered by the fact that the current cooling system is identified as the cheapest of all possible cooling system designs for JLD despite the potential for a 14% reduction in energy demand by introducing district cooling. This probably indicates that network piping costs are greatly overestimated in the current model's databases compared to energy carrier costs. While they don't seem as apparent based on this JLD analysis, other databases (e.g. component cost and the buildings' current cooling systems) likely also lack reliability.

Fundamentally, no multi-objective optimisation model evaluating systems as complex as district energy systems can fully be validated, as a complete validation would require the construction and operation of all possible energy systems for a given district. Hence, the best possible alternative is combining reliable data inputs with well-executed case studies.

The second shortcoming can be derived from the district cooling network layouts selected as the most energy-efficient for JLD (figure 6). The two networks overlapping in large parts would mean two pipes are exposed to ground temperatures and thus experience heat losses instead of just a single pipe. It's, therefore, very probable that fusing the two networks would result in fewer losses and, hence, a more energy-efficient system.

Very importantly, any genetic algorithm only identifies non-dominated solutions (i.e. the best among all *tested* solutions) and not the Pareto-optimal solutions (i.e. the best among all *possible* solutions). The fact that this solution was not identified likely indicates that the joint network solution was not tested in the search for optimal cooling systems. The search algorithm thus needs to be improved to become more thorough/efficient.

IV-B. Current Applications and Future Work

The results presented in III-C, and the figures in appendix A in particular, show that, given reasonable input parameters, the district cooling optimisation model can successfully identify cooling systems with compact supply systems, that strongly resemble the vast majority of systems currently in operation in Singapore. The scale of the solutions' overall system energy demand, heat emissions and cost also appear to be reasonable for a district such as JLD. Additionally, the model has been shown to successfully employ the principles of genetic optimisation and lead to a gradual improvement of the non-dominated set of solutions, rendering it more efficient than a random search. Manual intervention in the algorithm to propose new supply systems and network layouts to be evaluated has also shown to be of value.

In conclusion, the current model can very quickly identify a set of cooling system solutions for a district that might not be absolutely optimal but, at the very least, offer a good starting point for more detailed planning and engineering. With a few cycles of real-world application and improvement, it is very likely that this model will be able to accelerate the planning and engineering process for cooling systems in Singapore.

The goal for the next year of development is to find collaborations in districts where the introduction of district cooling is discussed. In an iterative process, solutions will be offered to planners and engineers working on these districts, and the model representations and parameters will be improved based on their feedback. Tests for automating human intervention in the algorithm, e.g. through the proposal of supply system and network layouts or cooling plant locations, will also be conducted.

APPENDIX A

OPTIMAL SUPPLY SYSTEMS FOR JLD

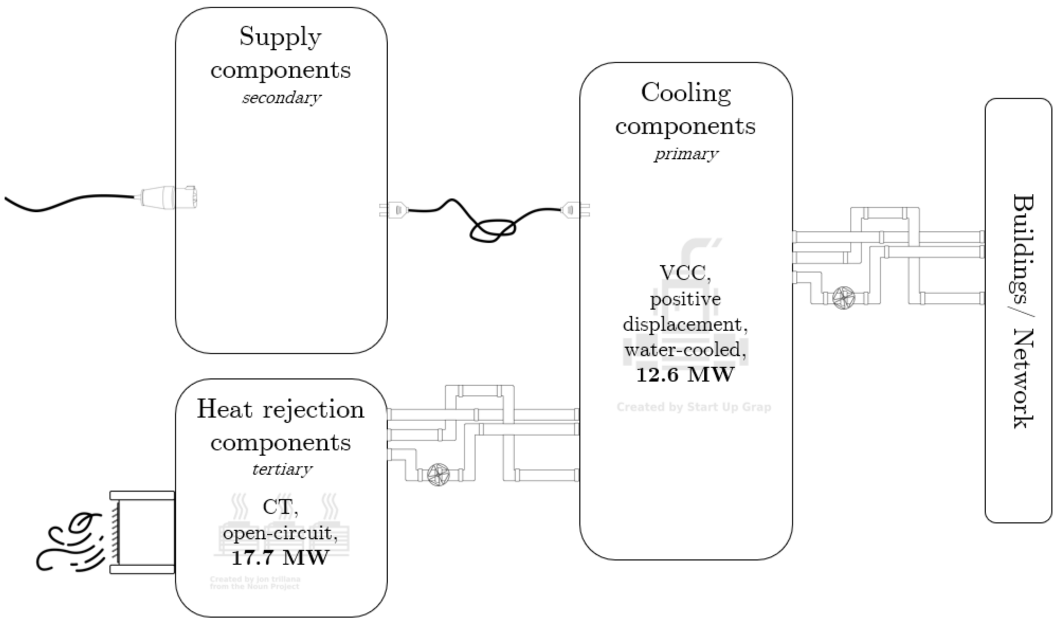

Fig. 8: *Energy-minimising solution: District cooling supply system for the network whose plant is located at the Science Center Singapore.*

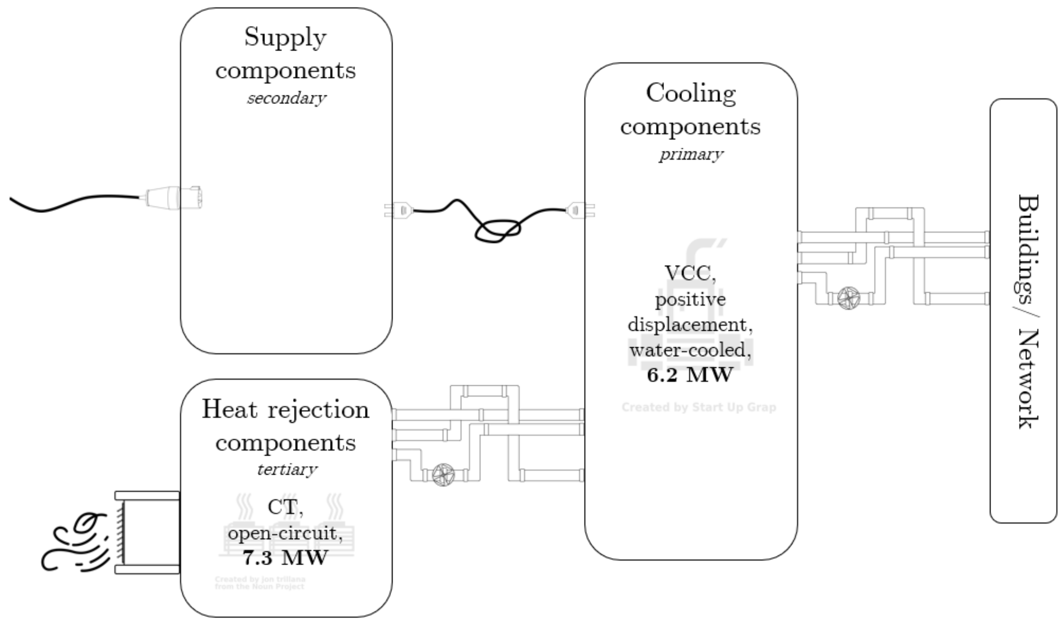

Fig. 9: *Energy-minimising solution: District cooling supply system for the network whose plant is located at the Jurong Town Hall.*

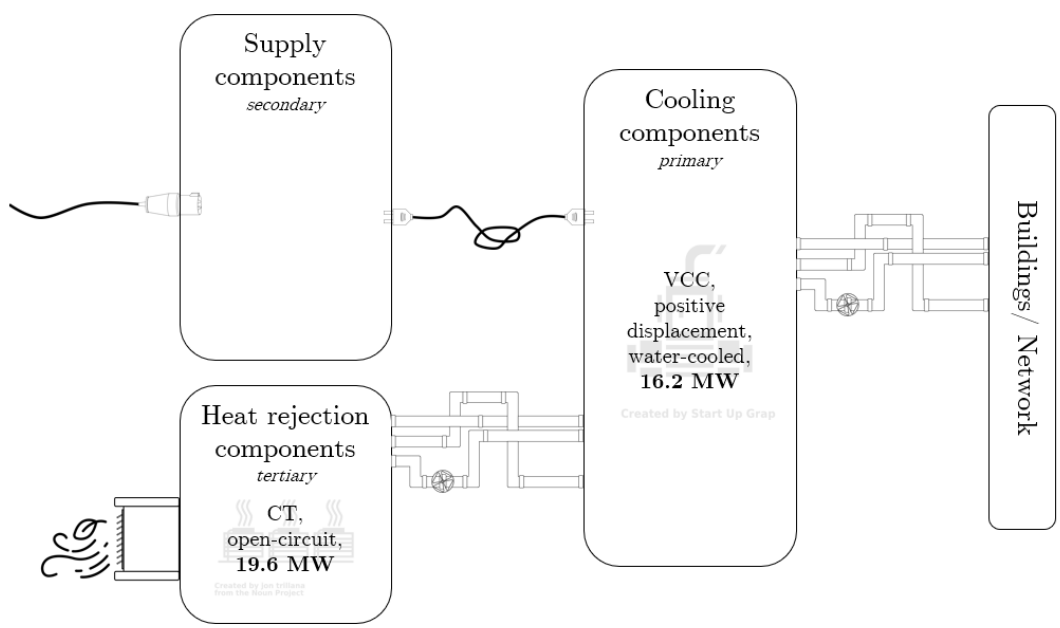

Fig. 10: *Supply system for the network on Jurong Lake's east side in the second-lowest-cost solution.*

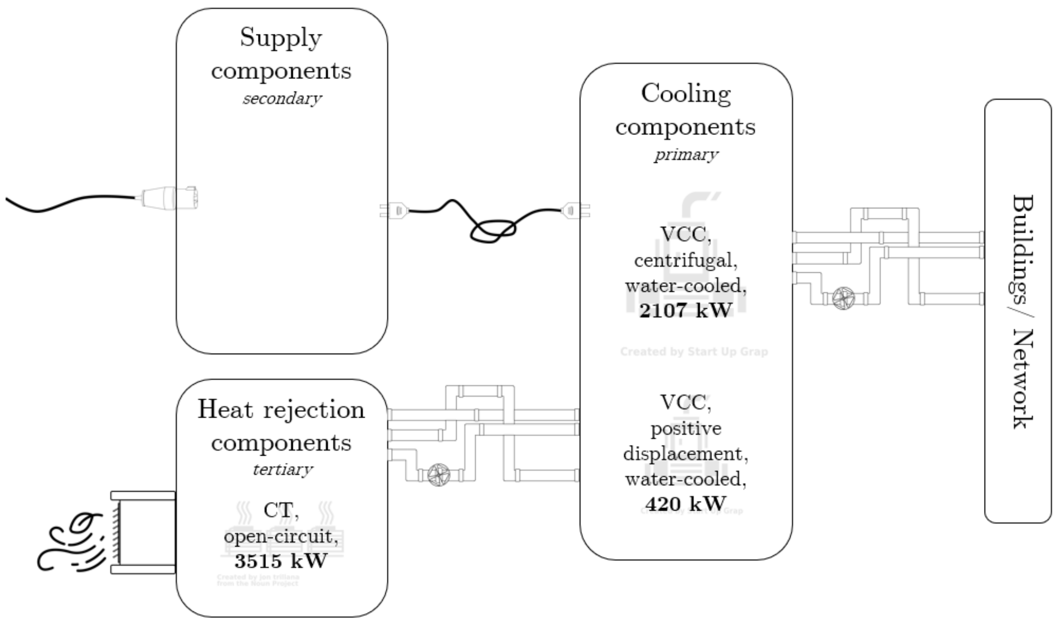

Fig. 11: *Second-lowest-cost solution: Supply system for the network on Jurong Lake's west side in the second-lowest-cost solution.*