

# THERMAL REQUEST OPTIMIZATION OF A SMART DISTRICT HEATING SYSTEM

A Thesis

by

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# THERMAL REQUEST OPTIMIZATION OF A SMART DISTRICT HEATING SYSTEM

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*To .....*

## ABSTRACT

This thesis proposes a solution approach to manage the heating plans of tenants served by a district heating plant located in Sweden to decrease the carbon footprint of the residents. To do that, the daily temperature request of each household in the associated pilot region is obtained, and the daily temperature profile of each household is optimized with the help of a decision support system and smart valves. The hot water inflow rates of radiators are remotely controlled via smart valves at each flat to minimize the total energy consumption, carbon emission and cost associated with the energy consumption of the district heating plant. We aim to shave the peak demands while fully satisfying the temperature requests of households without violating their thermal comfort. Peak demand shaving is achieved by generating preheating schedules via mathematical optimization and using the thermal storage potential of the insulated flats. The resulting mathematical optimization model presents significant computational challenges that cannot be efficiently solved using optimization solvers within a reasonable time limit. To this end, we adapt three genetic algorithm approaches that are computationally scalable for realistically-sized instances and verified to yield near-optimal solutions for the test instances. Extensive numerical analyses show the effectiveness of the proposed approach and the genetic algorithm since we yield significant carbon emission decrease and cost savings compared with the method that the experts of the utility company propose.

## ÖZETÇE

Bu tez dahilinde İsveç'te yer alan bir merkezi ısıtma sisteminin kullanıcılarının ısıtma planlarını kontrol ederek karbon ayakizini azaltacak bir çözüm sunulmaktadır. Yöntemin geliştirilmesi sırasında kullanılmak üzere pilot bölgedeki dairelerin gün içindeki sıcaklık talepleri elde edilmiş ve geliştirilen karar destek sisteminin akıllı vanalarla etkileşimi kullanılarak günlük sıcaklık profili eniyelenmiştir. Sıcak su içe akış oranı; merkezi ısıtma tesisinin toplam enerji tüketimi, karbon emisyonu ve enerji tüketimine bağlı gideri azaltmak amacıyla her daire için akıllı vanalar vasıtasıyla uzaktan kontrol edilmektedir. Belirlenen yaklaşımda, merkezi sistem kullanıcılarının termal konforlarını bozmadan ve termal taleplerini sağlayarak tepe sıcaklık talebi tıraşlaması hedeflenmektedir. Tepe talep tıraşlaması matematiksel eniyileme yöntemleri kullanılarak ve ısı yalıtımıyla desteklenmiş dairelerde ön ısıtma takvimleri oluşturularak sağlanmaktadır. Sunulan matematiksel eniyileme modeli, eniyileme çözümleri tarafından kabul edilebilir sürelerde verimli çözüm üretilememesine sebep olacak kadar yüksek hesap zorlukları içermektedir. Bu problemi aşmak için, gerçek hayat örneklerinde hesaplamalı olarak ölçeklenebilir ve optimuma yakın çözümler üreten 3 genetik algoritma yaklaşımı geliştirilmiştir. Sayısal analizler uygulanan yaklaşımların ve sunulan genetik algoritma adımlarının etkisi, sistemdeki karbon emisyonu ve enerji tüketimi giderlerinin, şirket tarafından geliştirilen uzman yöntemiyle karşılaştırılması sonucunda gözlemlenebilmektedir.

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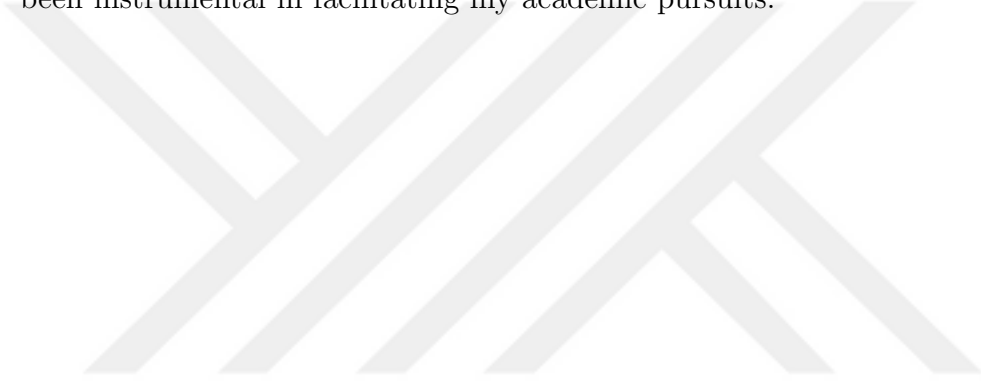
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# CHAPTER I

## INTRODUCTION

Rising levels of global carbon emissions jeopardize the future of the Earth. The increased frequency of disastrous weather conditions occurring worldwide is an early indicator of what is ahead regarding global warming. Policymakers aware of the unprecedented advocates are taking immediate action to abate carbon emissions worldwide. In this way, their goal is to limit temperature rise to well below  $2^{\circ}\text{C}$ , preferably to  $1.5^{\circ}\text{C}$ , compared to pre-industrial levels, as stated in the Paris Agreement, which was ratified or acceded by 187 states and the EU, representing about 79% of global greenhouse gas emissions (GHG) and came into force in 2016 [1]. Heating accounts for a significant proportion, nearly half, of modern society's energy consumption. Regrettably, air-polluting hydrocarbon-based fuels take the lead when it comes to residential heating, e.g., in the US, 38% of GHG emissions originate from residential climate control in addition to 15% that is for producing hot water [2]. Additionally, Zakeri et al. state that the COVID-19 pandemic and the Russian-Ukrainian war caused significant fluctuations in supply and demand curves [3]. Therefore, any effort to accelerate the decarbonization of residential heating systems and decrease costs is critical.

Optimized time-of-use through shifting energy demand that stems from higher room temperature or hot water requests is one effective way of achieving efficiency in residential heating. In other words, heat providers can facilitate greater efficiency once they adopt the method called peak shaving, i.e., shifting energy demand from peak times (time windows with maximized heating demand, e.g., the increase in hot

water demand due to morning shower) to non-peak times (time windows with minimized heating demand, e.g., the decrease in room temperature request due to absence of tenants at working hours). Peak shaving is particularly useful in district heating networks, which are prevalent in the Nordics. Usually, several energy sources, such as numerous heating plants powering the network with different fuel types, provide the required combustion. Although most utilities are obliged to use green resources (either carbon-free or at the very least carbon-neutral material), peak times become a severe challenge as plants struggle to meet the excessive heat demand only with environmentally friendly fuels. In such cases, plant operators are forced to run the backup boilers. The effort to meet peak energy demand usually results in the wastage of resources and higher carbon emissions because it is more resource-ineffective to maintain higher demand and switch to high-calorie carbon-emitting fuels. The recent advances in data-driven prediction and prescription technologies, internet-of-things (IoT), and cloud computing allow heat providers to control each specific node in their district heating network in real-time. Thanks to smart valves, thermostats, and comfort-aware heating scheduling algorithms, remote access to digitalized radiators paves the way towards fully or semi-automated and resource-optimal heating networks. With these technologies, one can design a personalized heating service in which tenants can interact with the heating system via a mobile application, submit their preferred temperature ranges for each room and for different time windows of the day and, as a result, enjoy having the optimal personalized heating settings which are not only comfortable enough but also environmentally friendly, applied automatically, without requiring them to make manual changes on the device.

Notice that the adverse environmental effects and the consumption cost increase exponentially as the number of active boilers increases at demand peaks. This thesis proposes a mathematical optimization model to control hot water inflow rates of radiators via smart valves and decision support systems (DSS) controlling tenant houses

remotely according to thermal requests of the tenants via a smartphone application and ensuring a balanced distribution of demand by generating optimized pre-heating schedules of homes in the pilot region. In this way, the aim is to minimize the boiler energy consumption of the district heating plant at peak demand hours (e.g., early hours in the morning and after 5 PM). The associated combinatorial optimization model can not be solved efficiently in less than 16 hours when the dimension of the problem is set for realistically-sized instances. To this end, we propose a metaheuristic with three approaches, namely, a traditional *genetic algorithm* (GA) and two downsizing approaches, to solve the associated model for large-sized instances. The proposed approach was implemented in a joint-force project with a leading utility in the Nordics region in a small town (Gustavsberg) in Sweden.

The remainder of the thesis is organized as follows. Chapter 2 provides the literature survey. Chapter 3 presents the solution methodology and technical details. Chapter 4 gives the numerical results of the proposed approach for synthetic data sets and the Gustavsberg case study. Finally, Chapter 5 gives the concluding remarks.

## CHAPTER II

### LITERATURE REVIEW

*In this chapter, we review the studies with a similar scope to ours; namely, we focus on those combining district heating with the thermal request or storage optimization and peak shaving. Several approaches are proposed to address thermal peak shaving in district heating systems. The approaches can be categorized into three main groups: black-box modeling, physical modeling, and optimization modeling.*

#### ***2.1 Literature Review***

Within the scope of black-box modeling, [4] proposed a multi-level approach to predict thermal requests at different levels (buildings, distribution network, and plant). Firstly, the authors used substation and meteorological data to predict heat demand at buildings with a black-box model. The black-box model is a linear model that outputs peak request, peak duration, and steady-state request from various parameters in the historical data. The authors also obtained the thermal request at the distribution network level by relying on the physical model, given the distribution network topology (characteristics of pipes and their interconnections). [5] used an artificial neural network (ANN) that optimizes supply air conditions to maintain desired room temperature by responding to characteristics of users in four different building types. Based on the past 62 years of outdoor temperature data, unmet demand (room temperature – set point temperature), and derivative of error, the ANN algorithm was trained to find the control pattern to maintain the room temperature. The model reduces peak energy demands in a district model by over 30%. [6] has proposed a three-staged algorithm for peak shaving in district heating plants that includes a

thermodynamic model for energy profile modifications, an agent-based model to represent temperature variations of individuals, and a reinforcement learning algorithm for optimality search between the prior stages by mediating the two needs. The result of this algorithm shows that the proposed approach reduces the peaks by 80%.

Physical modeling in district heating research refers to creating a scaled-down physical representation of a district heating system in a controlled environment. [7] proposed an optimization method to minimize the thermal peaks by optimizing the start-up time (anticipation time) of the heating system in the buildings. The maximum heat flux request of the distribution network represents the objective function. The heat flux is calculated by the total mass flow rate circulating in the network, relying on the supply temperature and the temperature of the water exiting the distribution network. [8] proposed a physical model for thermal peak load shaving through request variations of the users. The global heat load is calculated by simulating the start-up and shut-down schedules of the various buildings. The results show that it allows a reduction of up to 2.5 MWh/day of primary energy consumption through greater use of cogeneration and reduced boiler use. [9] proposed a physical optimization tool for peak shaving through user thermal requests changes. The optimization tool finds the best anticipation of the heating system start-up time to minimize the energy fraction boilers produce. The objective is to minimize the integral of the thermal power over time when the thermal power exceeds the cogeneration of maximum heat power. The results of the problem solved by GA show that the primary energy consumption reduction is about 0.8%.

The optimization modeling approach in the thermal request peak shaving problem returns to [10]. The authors proposed an energy optimization model named MODEST to investigate the impact of reducing heat demand on heat and electricity production. The objective function is a monetary cost and CO<sub>2</sub> emissions. The linear model finds

optimal heat demand reduction satisfying with energy efficiency measures. The result shows that the optimal heat demand reduction level for global CO<sub>2</sub> emissions is 30–35%. Similarly, [11] investigated how the heat load control, attic insulation, and electricity savings will affect the local energy system regarding economic and CO<sub>2</sub> impacts as well as the marginal operation of the district heating (DH) plants. They used the MODEST optimization model, and the objective function is to minimize the system cost of the DH system. They monitored the heat load control by using the heat inertia of buildings to reduce the peak load demand of the DH power plant (DHPP). The results show that heat load control is crucial for both the DH supplier and buildings. [12] proposed a model for predictive control of optimal operations of DHPP. Firstly, the power demand is forecasted from the historical data by generalized regression neural network using GA. Then, they integrated the forecast on fluctuating demand within the optimization problem and solved it in a receding horizon manner. The resulting problem was modeled as a mixed-integer linear program (MILP) and solved by the GLPK solver. At each time step, the optimization algorithm makes decisions on power plant operations, such as when each boiler unit should be started and stopped, when the storage device should be charged or discharged, and how long the controllable loads should be cut. It is verified that the model helps to manage demand peaks adequately. [4] proposed an optimization model for peak load shaving by obtaining the best start-up schedule of the heating systems through changes in the thermal request profiles of the users of buildings. The objective function is the energy fraction produced through boilers and the maximum heat load. The optimization problem was solved through GA. The numerical results showed that about a 1% reduction in annual primary energy consumption can be obtained without additional investment costs. Also, the authors applied clustering on the buildings by extracting the overall heat transfer coefficient and the thermal capacity of each building [13]. For each cluster, the maximum anticipation for the buildings belonging to each group

is calculated and added as a constraint to the optimizer. Each cluster minimizes the peak load via a GA-based approach, and the overall peak reduction was about 14%.

*Contributions* of this thesis to literature can be summarized in threefold:

1. Peak shaving optimization problem that aims to minimize the energy consumption cost of boilers using flat-level decisions via smart valve integration is first studied in this thesis.
2. We introduce three distinct GAs to address a complex combinatorial optimization problem. These GAs include the traditional GA and two downsizing approaches to partition the problem into manageable subproblems. The downsizing strategies involve breaking down the problem into two types of subproblems: horizontal and vertical. Horizontal subproblems can be solved simultaneously, while vertical subproblems are solved sequentially. We can generate high-quality initial solutions by incorporating the proposed downsizing approaches into the GA framework. As a result, our proposed GA achieves nearly optimal solutions for test instances with small sizes. Furthermore, it substantially improves solving realistically-sized problems, especially when the demand pattern exhibits a two-peak structure. The optimality performance of the proposed GA is verified via extensive numerical experiments that compare the objective function values of GA with that of the mathematical optimization model solved GUROBI optimization solver.
3. Extensive numerical experiments enriched by a real-life application show the effectiveness of the proposed method since we improve the energy consumption significantly to decrease the carbon emission and decrease the heating cost of boilers as high as **17%** for the best practice.

## CHAPTER III

### METHODOLOGY

*This chapter presents an integrated approach to optimize residential heating systems for enhanced energy efficiency. It comprises a Decision Support System (DSS), a Mathematical Optimization Model, prediction methods, genetic algorithm, and improvement heuristics. The DSS leverages advanced technologies like data-driven prediction and real-time control algorithms to offer personalized and energy-efficient heating solutions to individual households. The Mathematical Optimization Model considers various parameters, optimizing energy consumption while accounting for heating coefficients and boiler costs. We explore prediction methods, including AutoML pipelines, XGB, RF, and neural-network regressors, for accurate heating load predictions. The genetic algorithm optimizes the heating process, and innovative improvement heuristics enhance its performance.*

The essential tool that helps optimize the heating plan of a tenant heating plan is the smart valve that remotely controls the room temperature and reports room-level data at certain time points or specific events. More precisely, a smart valve modulates the mass hot water inflow rate to a radiator according to the difference in the temperature manually -by user- or remotely -by the DSS- set to the valve and actual temperature of the rooms at a given time. A higher mass flow rate results in a higher temperature gain for a lower rate in a specific time interval. When the room temperature is higher than the set temperature, the corresponding flow rate is set to zero, i.e., the radiator is off. Our experiments work with temperature profiles set by tenants using a mobile application that communicates with smart valves over the cloud. The associated hourly temperature profiles are assumed to be fixed for each

day unless users update them. An updated temperature demand will be activated the next day after a change. Therefore, we assume that the demand is fixed and known in a given planning horizon by the DSS proposed in this chapter. In practice, temperature profile patterns of the tenants resemble each other; more precisely, they demand higher temperatures in the early mornings of weekdays between hours 5:00–7:00 before they go to work and after they arrive back to their flats between hours 17:00–20:00. The resulting high demand of tenants may cause peak loads in the central heating plant when it is aimed to be satisfied just in time without utilizing the thermal storage of flats with preheating. For example, three boilers are activated at the district heating plant when the peak capacity is reached; nevertheless, using the maximum capacity is usually not intended because the cost of heating exponentially increases as more boilers are activated, which results in an increment to the carbon emission of the heating system. The aim is to keep the central heating plant with one or two active boilers at a time. Shaving the peak load can be achieved by storing the required heat energy before their demanded period and then using the associated thermal storage for shaving the extra load in peak demand periods instead of using boilers.

Ultimately, our goal is to propose the mathematical optimization model of the *smart district heating problem* (SDHP) that is explained above to find the optimal modulation settings of flats over the given finite planning horizon (a day) yielding the minimum heating cost while fully satisfying the thermal demand of tenants which also decreases the carbon emission. Notice that the modulation of a smart valve is controlled by deciding the value of the set temperature that may be remotely controlled with the DSS tool. Before we delve into the details of the mathematical optimization model, we propose the parameters and decision variables used by the model. The nomenclature is given in Table 1 below.

**Table 1:** Nomenclature for SDHP

---

<b>Sets</b>	
$\mathcal{J}$	set of flats – indexed by $j = 1, \dots, J$
$\mathcal{L}$	set of boilers – index by $\ell = 1, \dots, L$
$\mathcal{M}$	set of modes used for the radiator – indexed by $m = 0, \dots, 3$ (0:=“off-mode”)
$\mathcal{T}$	set of time periods in the planning horizon – indexed by $t = 0, \dots, T$
<b>Parameters</b>	
$C_{\ell t}$	cost of operating boiler $\ell$ at time $t$
$P$	penalty cost of shortage in demanded temperature
$P^b$	fixed cost of shortage in demanded temperature
$\epsilon_1$	acceptable temperature difference tolerance [°C]
$\epsilon_2$	maximum tolerance of unsatisfied demand [°C]
$L_{jt}$	heat loss of flat $j$ in period $t$ [°C]
$D_{jt}$	temperature demand of flat $j$ in period $t$ [°C]
$c_p^a$	heat capacity of dry air [joule/g°C]
$c_p^w$	heat capacity of water inside radiators [joule/g°C]
$a_j$	mass of air in flat $j$ [= $\rho A_j h$ ] [air density $\times$ meter-square $\times$ height ( $kg$ )]
$\dot{f}_m$	mass flow rate of radiator at mode $m$ [kg/s]
$T_j^{\text{sup}}$	the supply temperature of water in the inlet pipe of flat $j$ [°C]
$T_j^{\text{out}}$	the temperature of water in the outlet pipe of flat $j$ [°C]
$\Delta T_j$	:= $T_j^{\text{sup}} - T_j^{\text{out}}$ for flat $j$ [°C]
$Q_{\ell t}$	the capacity of boiler $\ell$ in period $t$ [J/s]
$K_j^0$	initial temperature of flat $j$ at the beginning of planning horizon [°C]
<b>Decision variables</b>	
$K_{jt}$	the temperature of flat $j$ in period $t$ [°C]
$S_{jt}$	the set temperature of flat $j$ in period $t$ at the smart regulator [°C]
$Z_{jt}^m$	1, if the radiator in flat $j$ operates in modulation $m$ in period $t$ 0, otherwise
$Y_{\ell t}$	1, if $\ell$ boilers are active at the district heating plant in period $t$ 0, otherwise
$U_{jt}$	amount of demand shortage in period $t$ in flat $j$
$W_{jt}$	1, if $\ell$ there is a demand shortage in period $t$ in flat $j$

---

The resulting MILP [SDHP] is given as the following.

[SDHP]:

$$\min_{\substack{K, S, U \\ W, Y, Z}} \sum_{t \in \mathcal{T} \setminus \{T\}} \left( \sum_{\ell \in \mathcal{L}} C_{\ell t} Y_{\ell t} + P \sum_{j \in \mathcal{J}} U_{jt} + P^b \sum_{j \in \mathcal{J}} W_{jt} \right)$$

$$\text{s.t. } K_{jt} \geq D_{jt} - U_{jt} - \epsilon_1 \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{0\} \quad (1)$$

$$U_{jt} \leq \epsilon_2 W_{jt} \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{0\} \quad (2)$$

$$K_{jt+1} = K_{jt} + \left[ c_p^w \Delta T_j \sum_{m \in \mathcal{M}} (\dot{f}_m Z_{jt}^m) - L_{jt} \right] \frac{1}{c_p^a a_j} \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (3)$$

$$c_p^w \sum_{m \in \mathcal{M}} \sum_{j \in \mathcal{J}} \Delta T_j \dot{f}_m Z_{jt}^m \leq \sum_{\ell \in \mathcal{L}} Q_{\ell t} Y_{\ell t} \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (4)$$

$$S_{jt} - K_{jt} - U_{jt} \leq 10(1 - Z_{jt}^0) \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (5)$$

$$10(Z_{jt}^1 - 1) \leq S_{jt} - K_{jt} - U_{jt} \leq 1 + 10(1 - Z_{jt}^1) \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (6)$$

$$1 - 10(1 - Z_{jt}^2) \leq S_{jt} - K_{jt} - U_{jt} \leq 2 + 10(1 - Z_{jt}^2) \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (7)$$

$$S_{jt} - K_{jt} - U_{jt} \geq 2 - 10(1 - Z_{jt}^3) \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (8)$$

$$\sum_{m \in \mathcal{M}} Z_{jt}^m = 1 \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \setminus \{T\} \quad (9)$$

$$K_{j0} = K_j^0 \quad \forall j \in \mathcal{J} \quad (10)$$

$$K_{jt} \geq 0 \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \quad (11)$$

$$X_{jt}, S_{jt}, U_{jt} \geq 0 \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \quad (12)$$

$$Y_{\ell t} \in \{0, 1\} \quad \forall \ell \in \mathcal{L}, t \in \mathcal{T} \quad (13)$$

$$Z_{jt}^m, W_{jt} \in \{0, 1\} \quad \forall m \in \mathcal{M}, j \in \mathcal{J}, t \in \mathcal{T} \quad (14)$$

The first component of the objective function minimizes the total cost of boilers supplying the given energy demand; the second and third components minimize fixed and variable penalty costs incurred when an unmet demand exists beyond the given tolerance level. Constraints (1) ensure that the demanded temperatures of the flats are satisfied over the planning horizon with a small tolerance. In cases where the required temperature cannot be attained (i.e.,  $U_{jt} > \epsilon_1$ ), an additional penalty cost

(P) is imposed in the objective function. Here, the thermal perception tolerance ( $\epsilon_1$ ) is chosen by the thermal comfort rate in low physical activity [14]. With the help of this, unnecessary activation of the fixed cost on the objective function has been prevented. Constraints (2) ensure demand satisfaction. If demand is not satisfied higher than the pre-determined thermal perception tolerance  $\epsilon_1$ , the system penalizes the unmet demand with the significantly high cost of  $P^b$ ; the same constraints also ensures that the unmet demand cannot exceed  $\epsilon_1 + \epsilon_2$ . Constraints (3) ensure the heat balance between the successive periods in the planning horizon, namely, the starting temperature of period  $t + 1$  is determined according to the heat generated in period  $t$  and the starting temperature of the period  $t$ , i.e., also referred to as the heat balance constraint. Depending on the selected modulation, a radiator transfers a certain amount of heat to flat  $j$ , which is equal to the product of the difference between the inlet and outlet temperatures of the water, the flow rate of the water, the specific heat capacity of the water, and the length of a period (see,  $[c_p^w \Delta T_j \sum_{m \in \mathcal{M}} (\dot{f}_m Z_{jt}^i)] \forall j \in J, t \in T$ ). Notice that some heat is lost and denoted by  $L_{jt}$ . Constraints (4) calculate the energy consumption of the flats in each timestamp by calculating the heat difference and determine the number of active boilers to supply requested energy at time  $t$ . Constraints (5)–(8) ensure the modulation of each flat  $j$  at time  $t$ , i.e., if the difference between the actual flat temperature and the temperature that is set on the valve is between  $[0, 0.5]^\circ\text{C}$ , then the mass flow rate is set to mode-1;  $[1, 2]^\circ\text{C}$  is set to mode-2; and  $[2.5, 5]^\circ\text{C}$  is set to mode-3. If the room temperature is higher than the valve reading, then the mass flow rate is set to mode-0 (off-mode). Constraints (9) ensure that only one modulation (mode 0–3) can be active in each flat  $j$ . Constraints (10) set the initial temperature at the beginning of the planning horizon. The remaining constraints enforce non-negativity and 0-1 variables.

### 3.1 Prediction Methods

The parameters  $(c_p^a, c_p^w, \Delta T_j, m_j, L_{jt})$  that are involved in the heat balance equation (3) and the energy consumption at each period presented in the left-hand side of constraints (4) are essential for accurately modeling the thermal behavior of individual flats. However, obtaining direct measurements of these parameters for each flat separately is challenging with the current configuration of the buildings. Nevertheless, leveraging smart valve technology, we have the opportunity to collect valuable data on the temperature updates at each flat  $(K_{jt})$  based on the given valve states  $(Z_{jt}^i)$  and the temperature profile of each household during the experiment, which includes additional parameters such as humidity and outside temperature. This data, combined with the knowledge of the experiment’s real-life settings, allows us to acquire information about each household’s surface area and dimensions. The experiment’s design in real-life settings further enhances the reliability and relevance of the collected data, as it reflects the actual conditions and habits of the residents. Additionally, having prior knowledge of each household’s surface area and dimensions helps us better understand how the thermal energy is distributed within the flats. By leveraging the available data and known parameters, we can develop a comprehensive and data-driven model to estimate the heat balance and energy consumption of each flat.

Within the scope of this thesis, we cannot publicly share the real data set used in this study due to a confidential agreement made by the company. Instead, we demonstrate our approach using a publicly available data set provided by Tsanas et al. [15]. The data set includes various time series data such as temperature, surface area, orientation, overall heights, and temperature coefficients. In our analysis, we focus on the heating load data and employ an automated machine learning (AutoML) pipeline to find the best regression models for predicting the behavior of heating load in systems where thermodynamic principles alone cannot fully explain the observed variations. Deviations from expected behavior can arise from measurement errors,

such as those caused by insensitive thermometers or errors in smart valve readings, as well as forecasting errors. While the scope of this thesis does not allow for the correction of measurement errors, we aim to address the prediction errors through our regression analysis. To begin, we conduct an explanatory data analysis (EDA) to gain insights into the data and identify the parameters that have the most significant impact on the heating load. EDA plays a critical role in ensuring the accuracy and reliability of subsequent regression analysis in predicting heating load behavior in residential buildings. Through our EDA, we observe that the volume of the area is directly correlated with the heat loss, which aligns with the expectations from the heating load equation. After performing the EDA, we develop an automated machine learning pipeline using the MLJAR library in Python. MLJAR is an AutoML tool that optimizes machine learning algorithms [16]. Using MLJAR, we train and fine-tune several regression models. The best-performing models for the given problem in our experiments were the extreme gradient boosting (XGB) [17], random forest (RF) [18], and neural-network regressors [19], which are nonlinear models. The AutoML pipeline trains these models, and their hyperparameter tuning is handled by MLJAR’s supervised machine learning library, which employs a grid search approach to explore candidate parameters. Although MLJAR does not utilize a Bayesian optimization process like AutoKeras for hyperparameter tuning, the grid search approach still leads to functional neural networks. Additionally, the tuned hyperparameters help to minimize the root mean square error (RMSE) values of the models. It is worth noting that the main focus of this thesis is on the nonlinear nature of these models rather than achieving the highest accuracy scores ( $R^2$ ). To compare the performance of the regression models, we evaluate their accuracy scores ( $R^2$ ) and present the results in Table 2.

The results show that XGB Regressor, RF Regressor, neural network (with 100 hidden layers, rectified linear unit activation function and constant learning rate), and

**Table 2:** Top 5 regression models for the heating data set

Model Type	RMSE Score	Accuracy Score
XGB Regression	0.802	99.3%
RF Regression	1.512	99.1%
Neural Network	1.718	98.5%
Decision Tree	2.293	97.8%
Linear Regression	3.276	93.1%

decision tree outperform the LR model in predictive accuracy due to their ability to capture and model nonlinear relationships within the data. However, the gap between the nonlinear and linear models is low. Hence, we choose to use linear regression to have a higher level of comparability between GA and mathematical optimization solver. Although the parameters obtained by nonlinear regression methods can be used in GA, using a nonlinear or random forest model leads to a drastic increase in the complexity of the mathematical optimization model. Additionally, as stated above, when the physical system follows the thermodynamic laws, with more accurate data and heat loss prediction, the resulting heating load formula is linear as in (3). The reader can refer to the GitHub link [20] for Python code of the prediction methods.

*Remark.* Notice that although we did not present the chosen methodology on our actual data set, the results obtained from the actual data set are similar to the accuracy metrics obtained by applying the AutoML pipeline mentioned above to data given in [15]. Python codes of AutoML pipeline can be found in [20].

### 3.1.1 Genetic Algorithm

We design a GA to solve [SDHP]. The distributed evolutionary algorithms in Python (DEAP) package [21] is utilized as the programming interface.

*Notation:* We adopt the same set, parameter, and decision variable definitions used in [SDHP] for the GA. To denote analogous decisions of different individuals in GA, we define  $\mathcal{I}$  as the individuals indexed by  $i$  ( $= 1, \dots, I$ ). The related index is

used in decision variables and parameters when needed. For example,  $K_{ijt}$  denotes the temperature for flat  $j \in \mathcal{J}$  of individual  $i \in I$  at time  $t \in T$  in GA, which is analogous to  $K_{jt}$  in [SDHP].

*A. Chromosome Representation:* Each individual is represented with a chromosome, yielding a solution for the problem. In our design, we use chromosomes with shape  $(J, T)$  where  $J$  is the number of radiators/flats and  $T$  is the number of time stamps in the planning horizon. The length of the planning horizon ( $H$ ) is determined in hours, and the time granularity ( $T_{\text{gran}}$ ) of the modulation decisions is determined in minutes; therefore, the number of timestamps is given by  $T = H \times 60 \times T_{\text{gran}}^{-1}$ . Each gene  $\ell$  in a chromosome of an individual represents a modulation of the smart valve in a given flat and can take integer values  $\{0, 1, 2, 3\}$ . According to a given modulation, the temperature profile of each flat can be determined according to heat balance equation (3), where the temperature granularity is set to two decimals (i.e., 0.00 C°).

*B. Generating Initial Population:* We uniformly sample  $I$  individuals. The size of the population is set to 500 in the numerical experiments.

*C. Fitness Function:* The goal of the problem is to minimize the cost of heating in the district heating boilers while meeting the tenants thermal requests. The following equation is used to evaluate the fitness score  $S_i$  of individual  $i \in \mathcal{I}$ :

$$S_i = \sum_{j=1}^J SUD_{ij} + SEC_i. \quad (15)$$

$SUD_{ij}$  denotes the total score of unmet demand at flat  $j \in \mathcal{J}$  of individual  $i \in \mathcal{I}$  in the planning horizon and calculated according to the following equation:

$$SUD_{ir} = \sum_{t=1}^T [P^b + P(U_{ijt} - \epsilon_1)] (U_{ijt} > \epsilon_1) \quad \forall i \in \mathcal{I}, j \in \mathcal{J} \quad (16)$$

where  $U_{ijt}$  is the unmet demand at flat  $j \in \mathcal{J}$  of individual  $i \in \mathcal{I}$  at time  $t \in T$  that is given by the following expression:

$$U_{ijt} = \max\{0, D_{jt} - K_{ijt}\} \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, t \in \mathcal{T}; \quad (17)$$

$SEC_i$  that is utilized in the fitness score denotes the total cost of energy consumption for individual  $i \in I$ , and calculated according to the following equation:

$$SEC_i = \sum_{t=1}^T CP_t \left( \sum_{j=1}^J EC_{ijt} \right) \quad \forall i \in I \quad (18)$$

where  $EC_{ijt} = c_p^w \sum_{m \in \mathcal{M}} \Delta T_j \dot{f}_m Z_{jt}^{im}$  is the energy consumption at flat  $j \in \mathcal{J}$  of individual  $i \in I$  at time  $t \in T$  calculated using the left-hand side of (4) according to the modulation level ( $Z_{jt}^{im}$ ). The boiler cost at time  $t$  is determined by a step function  $CP_t(\cdot)$  given as the following

$$CP_t(EC) = \begin{cases} C_{1t} & \text{if } EC \leq R \frac{EC_M}{6}, \\ C_{2t} & \text{if } \frac{EC_M}{6} < EC \leq R \frac{EC_M}{2}, \\ C_{3t} & \text{otherwise} \end{cases} \quad \forall t \in \mathcal{T} \quad (19)$$

where  $EC_M$  is the parameter that determines the boiler levels.

*D. Reproduction:* In the following text, we will elaborate on the particular method of genesis chosen for the thesis. It involves mutation, crossover, reproduction, and selection, which will be applied to the population of individuals under examination. In the case of reproduction, the process entails selecting an individual randomly from the population and pairing it with another individual belonging to the top 20% of the population, where fitness scores are used to rank individuals. The two individuals are combined to produce offspring with randomized characteristics, forming the basis of the next generation. The proposed reproduction algorithm crosses two individuals' gene values in a time horizon for the identical flat, i.e., randomly cutting 1D arrays from each individual and placing them on the other individual. To facilitate the distributed computing of all evolutionary processes, including reproduction, mutation, and selection, we employ *eamuPlusLambda* (ePL) function of DEAP. This reproduction will continue until 125 offspring individuals are generated at each algorithm replication.

*E. Mutation:* The probability of a gene mutation was set to 0.75 in our study. In the case of SDHP, minor changes in individuals do not result in significant improvements in the quality of solutions. Therefore, higher mutation probabilities were chosen to introduce sufficient diversity into the population. Additionally, if an individual is selected for mutation, it is first cloned to create a new individual, also referred to as an offspring. Cloning the initial individual before introducing any variations helps to maintain the accuracy of the fitness values, ensuring that suitable offspring are produced for further evolution. Furthermore, we customized the mutation boundaries based on the current value of the gene rather than adopting a uniform approach. Similarly, the mutation process will be repeated until 125 offspring individuals have been generated at each replication.

*F. Selection:* The ePL function implemented in DEAP is an evolutionary process that directs the population toward a specific target. This selection method employs a hybrid approach, utilizing elitism to retain the top-performing individuals from the prior generation while generating a random selection of offspring through mutation, crossover, and reproduction. The ePL function combines the best individuals from the previous generation with the newly generated offspring to produce a new population. In the first step, the individuals are ranked based on their fitness scores, and the top 400 are selected for the next generation. The remaining 100 individuals are selected through tournament-based elimination. Ten individuals are randomly chosen during the tournament phase, and the individual with the best fitness score is selected. The tournament-based elimination process is repeated until the desired population size of 500 is achieved.

*F. Termination:* The algorithm is halted upon reaching a predetermined number of replications, which is determined systematically in consideration of the problem size.

## 3.2 Improvement Algorithms

We explore additional improvement heuristics to enhance the solution quality of GA implemented using DEAP to solve SDHP for realistically-sized instances. Specifically, we consider two downsizing approaches for GA.

### 3.2.1 Multi-Row-Partitioning Downsizing Heuristic (MRPDH)

The solution quality of orthodox GA is affected when the dimension of the problem increases since the solution space of SDHP grows exponentially, and GA cannot span a significant portion of the solution space within the given time limit. To handle this bottleneck, we propose a multi-row-partitioning downsizing heuristic. This improvement heuristic divides the problem into horizontal subproblems and solves it using the same GA methodology proposed in Chapter 3.1.1. While dividing into subproblems, we use the following formula:

$$\tau = \begin{cases} 3, & \text{if } v > 4 \text{ or } \text{mod}(v, 3) = 0; \\ 2, & \text{otherwise} \end{cases} \quad (20)$$

where  $\tau$  represents the number of rows in the following subproblem to be created, while  $v$  denotes the count of unused rows from the original demand matrix up to the current subproblem. When the row count of the original demand matrix is greater than 4,  $\tau$  is set to 3. In other words, we prioritize 3 for  $\tau$  when  $v$  is greater than 4. However, when  $v$  equals 4, the demand matrix is divided into subproblems with a row size of 2, i.e.,  $\tau = 2$ . For instance, in a problem with dimensions 10 by 218, the generated subproblems would have dimensions of 3 by 218 ( $\times 2$ ) and 2 by 218 ( $\times 2$ ), respectively. We keep most problem-specific parameters unchanged, such as valve modulation limits, modulation energy consumption, and boiler cost. However, the boiler inflection points are proportionally adjusted according to  $\tau$  divided by the total number of flats ( $|J|$ ) to ensure a consistent cost structure for a subproblem. Once GA solves each subproblem in parallel, we merge them in the same order and re-solve

using the proposed GA methodology. This process provides us with a reasonable initial solution. After implementing the proposed algorithm, we observed significant improvements over the classic GA; further details will be presented in Chapter 4.

### 3.2.2 Dual-Column-Split Downsizing Heuristic (DCSDH)

It is important to note that the problem dimension and the size of the solution space are also influenced by the number of periods ( $|T|$ ) in the planning problem. As mentioned earlier, as the problem dimension increases, it poses a significant challenge for GA. In order to address this challenge, we have developed an enhancement strategy based on the assumption that there exists a specific time point ( $t$ ) during which none of the residential units require a substantial amount of energy consumption. The main challenge in DCSDH arises when such time intervals with low energy consumption cannot be found, leading to a loss of feasibility in the current solution. However, it is worth noting that in practice, heating demands from users tend to concentrate during early daytime and evening hours, while tenant temperature profiles typically remain relatively stable at lower temperatures around noon. Exploiting this observed pattern, we usually divide the GA evolutionary process into morning and afternoon phases. Although this assumption may not hold for all data sets, we often find a feasible division. Once such a period is identified, we partition the problem from the corresponding time point into subproblems based on columns and solve the downsized subproblems sequentially. The temperature values obtained from the first subproblem serve as inputs for the second subproblem, representing the starting temperatures. Finally, the second problem is solved using GA in the second phase. Later, the proposed solutions of both phases are combined and serve as an initial solution for the classic GA as before. To observe the effectiveness of the proposed algorithm, we refer the reader to Chapter 4.

### ***3.3 Implementing Improvement Heuristics to Genetic Algorithm***

In summary, the proposed approach combines MRPDH and DCSDH to improve the solution quality by decomposing the solution space and exploring a broader range of solutions via downsizing the planning problem at hand horizontally and vertically and leveraging the specific characteristics of the problem. More precisely, in the final GA algorithm, we first apply DCSDH to split the columns and then MRPDH to split the rows. For example, if the initial problem size is 9–216, the problem is first downsized to 9–108 ( $\times 2$ ) subproblems and then downsized again by rows into 3–108 ( $\times 3$ ) subproblems. Then MRPDH subproblems are solved in parallel, while the DCSDH splits are solved sequentially. Notice that all subproblems are solved more efficiently than the original problem because of their reduced sizes; moreover, the MRPDH subproblem can be parallelized since instances may be independently solved. In the final stage, the proposed GA is initialized by the solution from downsizing approaches. The numerical results presented below validate the effectiveness of the proposed approach for the standard GA.

## CHAPTER IV

### NUMERICAL RESULTS

This chapter first presents the comparison of *objective function value* (OFV) and CPU time performances of the proposed GA with those of Gurobi for synthetic data sets in Chapter 4.1. Next, we present a real-life implementation of the proposed approach over a case study. We show the effectiveness of our approach in different settings by analyzing the cost improvement made for the two benchmarks, namely, smart valves with no steering and smart valves with expert steering which will be explained in Chapter 4.2.

*Computer specifications.* The computational experiments are conducted on a 64-bit Windows computer with a 2.8 GHz Intel Core i7 CPU and 32 GB RAM. All computations were performed using the Python programming language. We use DEAP 1.3.3 to process GA and Gurobi 10.0 as the mathematical optimization solver.

#### ***4.1 Optimality and CPU time performances of GA***

In this chapter, we analyze the optimality performance of GA and compare the CPU time performances of GA and Gurobi optimization solver over instances of varying dimensions.

*Data.* We define six test instance types and generate five samples for each type. We set the number of flats to  $|J| = \{2, 4, 6, 8, 10, 16\}$  and the number of periods to  $|T| = 216$  and the time granularity is assumed to be 5 minutes, i.e., the planning horizon is assumed to be 18 hours (between 5:00–23:00). Inspired by the practice, the peak hours of 6:00 to 10:00 and 17:00 to 21:00 are randomly selected from the intervals  $[19, 22]$  °C with a granularity of 0.5 °C; and the off-peak hours are sampled from the interval  $[16, 19]$  °C. Subsequently, the collected data is subjected to post-processing

to mitigate abrupt fluctuations. The boiler costs for three levels ( $\ell = 1, 2, 3$ ) are given as  $\mathbf{C} = [5, 15, 40]$  that is always assumed to be fixed over the periods. The data sets used in this experiment for  $|J| = 16$  are available at [22, DH Data Set].

For each test dimension ( $|J|, |T|$ ), GA and Gurobi solve each instance, we report the (average) optimality gap percentage and CPU times of the final version of GA that adopts for multi-row-partitioning downsizing (MRPDH) and dual-column-split downsizing (DCSDH) heuristics presented in Table 3. **Each row of the table reports the average performances of the approaches over five different instances sampled according to the procedure mentioned above.** The individual performances of the proposed downsizing approaches are compared with orthodox GA presented in Table A1 of 5.1.

**Table 3:** Experiments

$ J $	$ T $	GA*	Runtime (sec)	
			GA	GRB
2	216	0.76%	2417	7200
4	216	5.28%	5169	14400
6	216	5.81%	4103	21600
8	216	8.37%	6774	28800
10	216	6.30%	7996	36000
16	216	18.31%	9473	57600

\* GA = MRPDH + DCSDH

The numerical results in Table 3 show that GA significantly outperforms the optimization software in CPU time. It is essential to point out that solving the mathematical optimization model SDHP with the commercial solver always takes more than the corresponding GA runtime hours for the given dimensions. Moreover, the optimality performance of GA is also as promising as its CPU time performance. The numerical results show that when  $|J| = 16$ , the optimality gap of GA is less than 18.3% (while the best-case performance is 17% and the worst-case performance is 19% among five instances generated), which is a high-quality solution given the significant CPU time performance improvement of the algorithm for Gurobi. In lower

dimensional instances, the optimality performance of GA is always less than 8.5%, and the algorithm works between 3 to 5 times faster than the commercial solver in all instances. Ultimately, we may conclude that GA yields near-optimal solutions at problem dimensions that the commercial solver can handle, and it provides high-quality solutions at realistically-sized problem dimensions that the commercial solver fails to provide a solution less than 16 hours.

## ***4.2 Real-life implementation of the proposed method***

In this chapter, we implement DSS that adopts GA proposed in this thesis in a real-life setting. The proposed approach is referred to as “proposed method”. We compare two benchmark approaches with the proposed one. The first benchmark is called “smart valves without steering”; this approach does not use any quantitative analysis. More precisely, the tenants pass the thermal demand via the mobile app, and smart valves regulate the radiators according to the given temperature requests without shaving the peaks to reduce the cost, i.e., only the inherent modulation mechanism of a smart valve is used. The second benchmark, referred to as “expert steering”, is proposed by the experts of the utility company. The associated approach is explained in detail below.

*Data.* Due to a confidential agreement with the utility company, we cannot share the real-life data sets used in the experiments presented in this chapter. Moreover, energy consumption charts are reported after scaling the data.

### **4.2.1 System Description**

The utility company that operates the district heating network in the test bed region at Gustavsberg regulates heat provision with substations. Heating is controlled at substations by changing the degree of heat exchange between the main pipe of the heat network — in which hot water that is heated up at the heating plant flows, and the building’s pipes. Individual flats may regulate their temperature through radiators.

Flat temperatures usually vary in the range of 17–25°C. The flats’ façade and tenants’ behavior, e.g., how often they open the window and the number of tenants who live in the same flat, are the factors that may affect the flat temperatures. Buildings are equipped with strong insulation support to minimize the effects of environmental factors. There are two buildings in the test bed, each with 16 flats, i.e., the total number of flats is 32.

The associated buildings have undergone technological infrastructure updates just before tests are initialized; smart valves with remote control and thermal sensors are installed in the flats, and essential data is collected from flats and buildings. The goal is to achieve optimal or near-optimal heating plans for tenants while fully satisfying their temperature demands without violating their thermal comforts. As mentioned before, shaving peak demand is the ultimate goal because the energy consumption of boilers increases exponentially as the number of active boilers increases, resulting in high costs for the company and a larger carbon footprint, as mentioned before. The experts of the district heating plant suggest one or (in the worst-case) two active boilers at a time, and having three active boilers is usually not intended.

The utility company charges tenants a monthly fixed rate for the heating service. Thus, tenants have no financial incentive to optimize the heating regime of their flats through set temperature changes made on the radiators. However, the utility company has a solid financial and environmental motive to intervene and make such resource-effective changes. However, their intervention should ideally not create any thermal discomfort for the tenants. The buildings are equipped with smart valves and thermostats that allow real-time measurement and control of room temperatures, both as precise as 0.1°C and inhabitants living in these flats are provided with a mobile application, i.e., shortly referred to as “app”, that allows real-time room temperature monitoring and control, as well as feedback provision, i.e., tenants, can control room temperatures using the app and give feedback about their preferred

room temperature with an hourly resolution. Most importantly, the smart valves installed in the buildings may be remotely controlled over the cloud, and hence one may use more advanced methods to regulate the temperatures in these flats.

#### **4.2.2 Expert Steering Approach**

The utility company's experts employed a five-stage steering approach to shave peak demand prior to the implementation of the DSS tool (proposed method) described in this research within the region. This approach is not planned to function as a standalone peak shaving method. Instead, it aims to regulate and minimize excessive temperature requests from tenants in a controlled manner. In this context, a mobile application referred to as "app" obtains tenants' daily temperature preferences. They are informed that their temperature profiles may be remotely adjusted if necessary, and they are encouraged to provide feedback through the same application if the expert steering impacts their thermal comfort.

Stage 1 Initialize target temperatures exceeding  $25^{\circ}\text{C}$  as  $25^{\circ}\text{C}$  for each residential unit.

Stage 2 Set target temperatures of time stamps that are  $2^{\circ}\text{C}$  higher than the average predicted temperature of each flat to the average temperature plus  $2^{\circ}\text{C}$ . Keep the target temperatures below this threshold unchanged.

Stage 3 Decrease the target temperatures of each flat that are higher or equal to  $19^{\circ}\text{C}$  by  $1^{\circ}\text{C}$ .

Stage 4 Reduce the target temperatures of each flat, which has an average predicted temperature higher than  $23^{\circ}\text{C}$ , by  $1^{\circ}\text{C}$  unless the target temperature is less than  $18^{\circ}\text{C}$ .

Stage 5 Adopt the procedure in Stage 4 for flats those have an average predicted temperature higher than  $22.5^{\circ}\text{C}$ .

Stage 6 Apply the same approach for flats that have an average predicted temperature higher than  $22^{\circ}\text{C}$ .

The above-mentioned stages of the expert steering approach can also be implemented by utilizing real-time temperature measurements instead of relying on prediction models. However, each algorithm stage will require at least one day when actual temperatures are employed. Therefore, the execution of the final temperature profile derived from the proposed approach may impact tenants' comfort if there is a significant time gap between the start and the completion of the expert steering. This is due to the potential changes in demand patterns and weather forecasts that can occur over time. This is why to adopt the final temperature profile of the expert steering approach for each flat daily, and we recalculate temperature predictions according to temperature profiles that are revised after each stage of the algorithm. The expert steering algorithm will be used as the main benchmark of the method that is proposed in this thesis.

### 4.2.3 Case Study

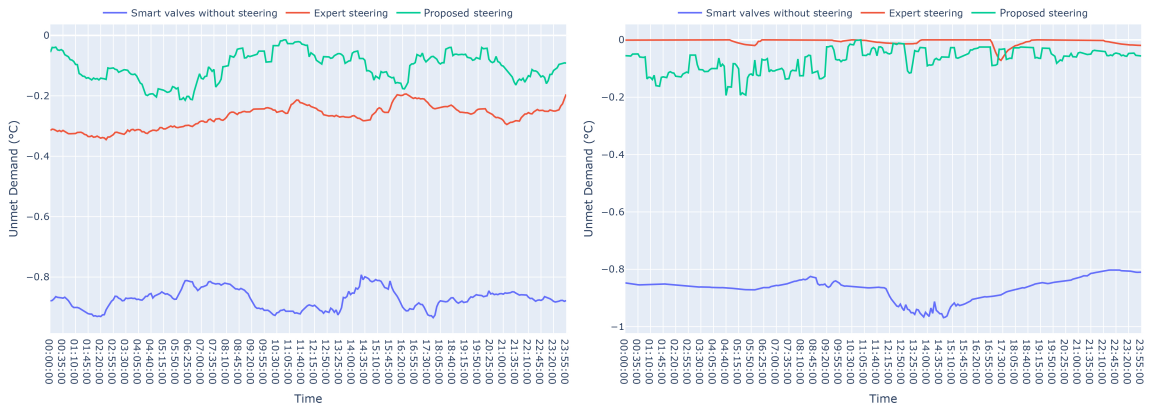
The associated experiment was held on 20–26 May 2020 at two buildings equipped with smart valves and the mobile app. Each method, namely, the proposed DSS called proposed steering, expert steering, and smart valves without steering, are implemented in building 1 on days 1–2, 3–4, and 5–6, respectively. For the same two-day periods, the methods are implemented in expert steering, smart valves without steering, and proposed steering order in building 2. Figure 1 shows the daily average energy consumption (kWh) of each method collected in two days over a 24-hour time horizon for the two buildings. Figure 2 presents the average unmet demand ( $^{\circ}\text{C}$ ) of the proposed heating plans of the associated approaches. Finally, Figure 3 gives the percentages of the valve states as pie charts for each method.

The numerical results in Figure 1 reveal that both expert and proposed steering



**Figure 1:** Energy consumption charts for buildings 1 (left) and 2 (right)

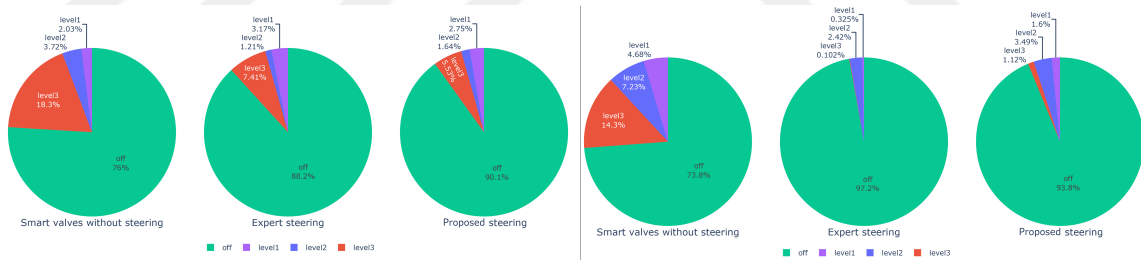
approaches yield significant improvements for the smart valves without steering case (i.e., when no quantitative analysis is used in the smart valve heating plans). The associated energy consumption improvement is as significant as %30 and %35 for expert and proposed steering, respectively. When we compare the proposed method with the expert steering, the total energy consumption is improved by more than %17 while the peak energy consumption is reduced from 1.1 kWh to 0.95 kWh yielding an improvement as high as %13. Next, we compare the comfort of tenants under the three different heating plans implemented in practice generated by the three methods.



**Figure 2:** Unmet demand chart for buildings 1 (left) and 2 (right)

Notice that proposed steering works more proactively than expert steering and no steering methods; proposed steering aims to provide a requested temperature in

time or before the given temperature profile. On the other hand, expert steering and no steering methods wait until the temperature updates in the given user profiles are realized. Late updates might fail to meet demands on time since associated methods work reactively. The numerical results in Figure 2 show that (average) unmet demand for smart valves without steering is between  $0.9^{\circ}\text{C}$  and  $2.75^{\circ}\text{C}$ . At the same time, the associated value is always less than  $0.25^{\circ}\text{C}$  for proposed steering and between  $0.3^{\circ}\text{C}$  and  $0.6^{\circ}\text{C}$  for the expert steering method. Lastly, even though the DSS based on the SDHP model aims to satisfy the demand, it may not meet the demand as in the given experiments. As may be anticipated, this is caused by prediction errors in the regression coefficients of the heat balance constraint (3). It is worth mentioning that tenants do not give negative feedback through the mobile app on proposed and expert steering approaches throughout the experiment because their thermal comfort is not affected by the proposed approach.



**Figure 3:** Valve states in buildings 1 (left) and 2 (right)

Another important indicator that shows the validity of the proposed approach is the percentage of valve states. Two buildings in our experiments have strong insulation, so flats may be used as thermal storage when flats (pre)heating plans are made systematically. Numerical results in Figure 3 show that proposed steering increases the percentage off-state from %76 to %90 compared with when only smart valves are used. The associated improvement is even more significant in building 2 since the percentage of off-state increases from %59 to %90. When we compare expert steering with proposed steering, both approaches are very close in the percentage of

off-state, but proposed steering still outperforms the related method between %2 to %5 difference in the rate of off-state. Ultimately, the associated improvement is significant and manifests the validity of the proposed approach because smart valves work more efficiently when they are proactively planned to work according to the given demand and consumption parameters. In the following chapter, we summarize the managerial implications of this thesis.



## CHAPTER V

### CONCLUSIONS

This thesis proposed an optimization approach to minimize the total energy consumption cost of a smart district heating system that employs smart valves. The resulting problem was computationally and financially expensive to solve with commercial solvers within the given time limit. Therefore, a genetic algorithm (GA) was proposed to solve the resulting optimization model, and data science methods were used to predict the temperature profiles of flats. The effectiveness of the proposed method was demonstrated through numerical experiments, which showed that the total savings achieved by the decision support system (DSS) could reach as high as 17% compared with the best practice. In the remainder of this chapter, the managerial implications of this research, highlighted in italics in each paragraph, are discussed.

*The practical benefits of using GA* in the decision-making process can be explained threefold: First, the developed approach enables proactive planning and identification of potential issues during the initial planning phase. Moreover, it facilitates the re-application of the method and the adjustment of decisions in response to unforeseen circumstances when needed, surpassing expert guidance's capabilities and the independent performance of smart valves equipped with the proposed DSS. Therefore, the improved CPU time performance that GA enables is critical in practice. Second, it may be more efficient to adopt different prediction methods, such as automated machine learning packages documented in Python, to GA than implementing the associated tools to the optimization model since resulting prediction models may

significantly increase the mathematical optimization complexity of the orthodox optimization model even though it usually does not affect the performance of GA. Third, the per-use or yearly cost of using a commercial solver may be larger than the improvement made in small regions like Gustavsberg, i.e., investing in a commercial solver may not be financially feasible since the proposed GA is free of charge.

Although we cannot provide actual carbon emission data, we can report *the estimated reduction in CO<sub>2</sub> emissions* using our approach. Based on the study by Bertelsen and Mathielsen [23], the average annual heat consumption for residential buildings is projected to be 124 kWh per square meter. Assuming that the cost coefficients utilized in their and our research do not have significant prediction errors, our approach results in a yearly energy savings of 26,982 kWh ( $124 \times 80 \times 16 \times 17\%$ ) per building. Moreover, the Ministry of Infrastructure has reported that Sweden’s carbon intensity in 2015 was 0.029 g CO<sub>2</sub> per kWh [24]. Based on the information given above, when compared to the best-practice benchmark (i.e., the expert steering approach), our approach leads to a minimum reduction of 782 kg ( $26,982 \times 0.029$ ) of CO<sub>2</sub> emissions per building per year, which is a significant reduction for a building comprising 16 apartments.

Notice that the DSS tool proposed in this research has been successfully implemented in real-world scenarios by *incorporating smart valves and thermostats* that can be controlled remotely through cloud infrastructure. Therefore, we strongly advocate adopting smart valves, as they facilitate the seamless integration of quantitative methods into residential units. In addition, smart valves often come with mobile applications, empowering users to manage their daily heating schedules. For more detailed information on the smart valve systems employed in this study, please refer to the website <https://smartcosa.com/intl/>[25]. It is crucial to recognize that without the establishment of the smart valve infrastructure, the method developed in this article would not have had the opportunity to be put into practice.

Furthermore, it is crucial to highlight that the distributed planning of pre-heating schedules achieves the cost savings attained through the proposed framework, which is made possible by the *insulation and thermal storage capabilities of the buildings* in Gustavsberg. Thus, the thermal storage potential of the residential units serves as a prerequisite for the effective application of the aforementioned technological and quantitative methods detailed in this thesis.

The developed method does not have a perspective to distribute the costs of apartments equally. Therefore, when deriving an optimal heating plan, the costs of some apartments may consistently remain high because there can be multiple alternative optimal solutions to the problem, and there is no constraint on distributing the costs more equitably. As a result, *the developed method produces more practicable solutions for fixed payment systems* like in Gustavsberg.

Finally, our system has been designed based on pre-recorded heating plans on a daily basis, and manual interactions by the tenants with the smart valves are not included within the data set, and this information is not used by the method. As a result, there is no mechanism in place to verify the *occupancy status of tenants* in their respective apartments. This deliberate omission of tenant occupancy verification addresses potential *ethical considerations* associated with the proposed method.

## 5.1 Experiments

**Table A1:** Experiments

$ J $	$ T $	GA	MRPDH	DCSDH	Runtime (sec)			
					GA	MRPDH	DCSDH	GRB
2	216	0.76%	0.76%	0.76%	1612	2318	2417	7200
4	216	10.68%	4.88%	5.28%	1718	3633	5169	14400
6	216	47.54%	5.34%	5.81%	1911	3901	4103	21600
8	216	112.75%	15.16%	8.37%	2389	4893	6774	28800
10	216	103.52%	10.98%	6.30%	2814	6447	7796	36000
16	216	155.85%	19.11%	17.32%	3272	8253	12245	57600

The CPU times and optimality performances reported in Table A1 can be interpreted as follows: “GA” columns denote the optimality gap and CPU times performances of the orthodox GA algorithm when no downsizing approach is used; “MRPDH” columns denote the same when the row-based downsizing heuristic is used, and the resulting subproblems are solved in parallel and combined to yields the initial solution of the GA that will run in the final stage; and ”DCSDH” columns denote when row-based and column-based downsizing approaches are used simultaneously while row subproblems are solved in parallel, and column subproblems are solved sequentially to ultimately generate the initial solution of GA that will run afterward. The optimality gap percentages of GA, MRPDH, and DCSDH are reported for the objective function values of the Gurobi optimization solver that is run with a time limit of 56000 seconds. The run times of downsizing approaches include both the running times of the downsizing approach and GA, which is initialized with the solution of the downsizing approach. The numerical results are the average performances of five instances, as in Chapters 4.1 and 4.2.

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## VITA

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