Abstract—Modern day District Heating and Cooling (DHC) networks are complex interconnections of heat energy sources and heat energy consumers wherein the available energy from the sources is networked to the consumers for meeting their space heating (or cooling) requirements. Often, the energy sources are renewables and thermal run-off from industrial processes which are intermittent. Under extremely exigent conditions (such as very low ambient temperatures), these DHC networks may potentially suffer from energy supply inadequacy. Subsequently, selfish uncoordinated control of heat energy inflow at distributed consumer premises can lead to unfair allocation of the already inadequate energy to different consumers, potentially leading to consumer disgruntlement. Factors such as thermal losses in the network, varying levels of building insulation and different building heat capacities only exacerbate these issues. In this paper, we propose a policy for implementing Demand Response (DR) in DHC networks with an objective of optimizing different fairness based objectives. Specifically, our proposed algorithm estimates dynamically evolving building thermal parameters from continuously recorded temperature sensor measurements from different points in the network. It then uses this knowledge to suggest suitable control of network parameters such as mass flow rate of fluid to the buildings in order to realize the network level thermal fairness based objectives.

I. INTRODUCTION

District Heating and Cooling (DHC) networks (also known as thermal grids) are complex interconnections of heat energy sources and heat energy consumers where the energy is networked from the source to consumers through pipes by means of a fluid (say hot water). Consumers use this energy to meet their space heating (or cooling) and hot water requirements. The main advantages of such networks lie in their ability to recycle waste heat from industrial processes, increased reliability, ability to reduce emission levels, increase flexibility of operation, reduce life cycle costs, and capital costs and their ability to integrate renewable energy. They are extremely relevant in countries with frigid climatic conditions such as Finland, Norway and Sweden. Overall in Europe, it has been estimated that around 62 million consumers are served by these thermal grids totaling about 12% of the entire population [1]. DHC networks initially started out as steam networks in late nineteenth century where supply temperatures close to 200°C were used. These largely inefficient systems have evolved over the years to have higher operational efficiencies, lower supply (water) temperatures and integrated renewable energy sources [2], [3].

However, even for modern day networks, the excessive demand of energy coupled with supply side inadequacies (partly due to the intermittent nature of renewable sources) can potentially affect the optimal operation of these grids. Moreover, uncoordinated and selfish control of thermostat set-point in distributed consumer premises may make energy allocation unfair thus increasing consumer disgruntlement. To overcome this supply inadequacy, the DHC network utility then has to resort to procuring energy from uneconomical and possibly fossil-fuel based expensive peak plants hence making system operation uneconomic. To avoid such scenarios, it becomes imperative that these utilities find a solution to impart thermal fairness among consumers under the existence of supply side inadequacy. This throws open the avenue for development of appropriate DR strategies in a DHC network.

Existing research in the domain of thermal grids has till date mostly focused on optimizing overall cost of operation, energy efficiency or supply water temperature of the network. In [4], a mass flow rate control method for improving energy efficiency has been presented. Authors in [5] have developed optimal control strategies to minimize fossil fuel consumption in an integrated district heating system with availability of renewable energy sources like solar energy and wind energy. An approach for system cost minimization along with minimization of energy consumption for an entire year in district heating networks through a case study has been presented in [6]. Similar studies for modeling and optimization of operational cost for thermal grids have been proposed in [7]. A detailed modeling of a thermal grid along with a mass flow control methodology to achieve appreciable temperature cooling has been proposed in [8]. The subject of supply temperature optimization has been dealt with in several papers such as [9], [10] and [11]. Authors in [9] propose a predictive control scheme using fuzzy Direct Matrix Control (DMC) for optimizing supply water temperature in district heating networks. Authors in [12] highlight the importance of properly selecting the control period for controlling the supply temperature of water. Authors in [13] discuss a methodology where mass flow rates and supply water temperature are optimized to minimize heat loss rate in thermal grids. While the above optimization problems are extremely relevant in the context of DHC network operation, there is still a need to investigate the potential for DR to ensure fairness within thermal grids.

In our previous work [14], we modeled a district heating
(DH) network based on physics-based thermodynamic principles and proposed a centralized DR scheme for achieving network level thermal fairness objectives. We had considered that the thermal parameters of the buildings, which are essential in optimizing the fairness metric in the DH network, were known to the central utility a priori. However, in reality we understand that such parameters are not only hard to estimate but also dynamically varying on a slow time scale. Hence, in this work, we enhance our DR scheme proposed in [14] (which assumes that all critical building thermal parameters are known) by considering the practical challenge of building thermal parameter estimation. This new scheme dynamically estimates the building thermal parameters from centrally recorded temperature sensor data from various points in the network. It then uses these estimated parameters for computing the optimal mass flow rates (DR signal) to be channeled to different buildings for realization of network level fairness based objective.

II. MODELING THE DISTRICT HEATING NETWORK

We consider a district heating network as shown in Figure 1. Let \( N_b = \{1, 2, \ldots, n\} \) represent the set of all buildings in the DH network. We assume a simple parallel topology to define the connectivity of the buildings in this network. Each building \( i \in N_b \) is assumed to have a thermal capacity \( C_i \) and an effective thermal insulation given by \( R_i \). We assume that the energy distribution in buildings are subjected to thermal loss, which typically increases with their distances from the heat source. The heat source is assumed to be receiving cold return water at a temperature of \( T_R \), and using the input power \( Q_{in} \) is able to heat the water up to a supply temperature of \( T_S \). Note that in reality, the hot water supplied to the building would be used for both space heating and tap water purposes. However, the demand for the latter is typically negligible in comparison with the earlier, and hence in this work, we assume that the hot water is entirely consumed for space heating purposes.

The heated water is networked through the connection of pipes to individual buildings as shown in Figure 1. During this transport, the thermal losses incurred along the way causes the effective supply temperature available (\( T^i_{MS} \)) at the mains (primary side) of the heat exchange circuit in building \( i \) to be less than \( T_S \), i.e. \( T^i_{MS} = T_S + w_i \) where \( w_i < 0 \) is the thermal loss (loss in temperature of supply water) incurred for building \( i \). The effective incoming heat energy from the water is transferred to the house side (secondary side) of the heat exchange circuit which then has a supply temperature of \( T^i_{HS} \). It must be noted that \( T^i_{HS} \leq T^i_{MS} \). For our case, we assume that \( T^i_{MS} - T^i_{HS} = \delta \), \( \forall i \in N_b \), where \( \delta \) is the temperature differential between \( T^i_{MS} \) and \( T^i_{HS} \). The hot water in the secondary side is now circulated through the radiators of the building (HVAC equipment) \( i \) to provide for space heating and ideally maintain the ambient zone temperature \( T^i_z \) of that building at a preferred set-point \( T^i_{set} \). The return cold water temperature in the secondary, i.e. \( T^i_{HR} \), determines the return temperature in the mains i.e. \( T^i_{MR} \). Subsequently the loss-adjusted return temperatures of the buildings i.e. the \( T^i_R, \forall i \in N_b \), determine the effective return temperature \( T^i_R \) of the water at the heat source.

A. Modeling of individual building thermodynamics

In this section, we attempt to capture the detailed thermodynamics of each individual building \( i \in N_b \), depending on several factors including its effective equivalent thermal parameters \((R_i \text{ and } C_i)\), its heat exchanger effectiveness \( \epsilon_i \), the respective supply and return temperatures in the primary and secondary of the heat exchanger circuit of the building, its radiator characteristics (including its thermal conductivity \( U_i \) and effective surface area \( A_i \)), and the ambient temperature \( T_{\infty} \). Note that there are two heat exchange circuits: (a) \( HE_1 \) which captures heat exchange between the network pipes (primary/mains) and the house pipes (secondary), and (b) \( HE_2 \) which captures the heat exchange between the house pipes and the indoor house space through the radiator coils. We begin with the indoor zone temperature evolution. We assume that the indoor zone temperature (\( T^i_z \)) of a building \( i \) evolves according to,

\[
T^i_z = \frac{1}{R_i C_i} (T^i_{\infty} - T^i_z) + \frac{1}{C_i} \dot{Q}^i_{in} + \frac{1}{C_i} \dot{Q}^i_{HV AC}. \tag{1}
\]

Here, \( \dot{Q}^i_{in} \) is the power generated by active elements (such as humans, lighting devices etc.) within building \( i \) and \( \dot{Q}^i_{HV AC} \) is the HVAC power available through the radiator of building \( i \) for indoor space heating. Usually the \( \dot{Q}^i_{in} \) for buildings is much smaller in comparison with \( \dot{Q}^i_{HV AC} \), so we assume \( \dot{Q}^i_{in} = 0 \) unless otherwise specified. Now, note that

\[
\dot{Q}^i_{HV AC} = \dot{m}^i_{HS} C_p (T^i_{HS} - T^i_{HR}), \tag{2}
\]

where \( \dot{m}^i_{HS}, T^i_{HS} \text{ and } T^i_{HR} \) are the mass flow rate, supply and return temperatures of the water in the secondary of \( HE_1 \) circuit respectively. \( C_p \) is the specific heat capacity of water. The effectiveness of heat exchanger in the \( HE_1 \) circuit is modeled according to,

\[
\frac{T^i_{MS} - T^i_{MR}}{T^i_{MS} - T^i_{HR}} = \epsilon_i, \tag{3}
\]

where \( \epsilon_i \) is the heat exchanger effectiveness in building \( i \). Note that \( 0 \leq \epsilon_i \leq 1, \forall i \). The radiator heat exchange dynamics in \( HE_2 \) circuit is governed by the equation,

\[
\dot{Q}^i_{HV AC} = \dot{m}^i_{HR} C_p (T^i_{HS} - T^i_{HR}) = U_i A_i (\Delta T^i_{eff}), \tag{4}
\]

where \( \Delta T^i_{eff} \) is the temperature difference between the radiator coils and the indoor ambient in building \( i \). The \( \Delta T^i_{eff} \) can be approximated as \( \Delta T^i_{eff} \approx \frac{(T^i_{HS} + T^i_{HR})}{2} - T^i_{z} \) for practical purposes. Finally, assuming perfect insulation at substation heat exchanger (no energy loss between primary side and secondary side), we can also write,

\[
\dot{m}^i_{HS} C_p (T^i_{MS} - T^i_{MR}) = \dot{m}^i_{HR} C_p (T^i_{HS} - T^i_{HR}) \tag{5}
\]

where \( \dot{m}^i_{HS} \) is the mass flow rate of water in the primary/mains of \( HE_1 \) circuit.
B. Modeling of network thermodynamics

Assume that $\hat{Q}_{in}$ is the total rate of heat energy available at the central source for district heating needs. From conservation of energy in the overall district heating network, we can write $\hat{Q}_{in} = \sum_{i\in N_0} \dot{m}_{s,i}C_p(T_s - T_{R,i})$. Noting that $\hat{Q}_{in} = MC_p(T_s - T_R)$, where $M = \sum_{i\in N_0} \dot{m}_{s,i}$, we can express the return temperature of water ($T_R$) in the network as,

$$T_R = \frac{\sum_{i\in N_0} \dot{m}_{s,i}T_{R,i}^j}{\sum_{i\in N_0} \dot{m}_{s,i}} = \frac{\sum_{i\in N_0} \dot{m}_{s,i}T_{R,i}^j}{M}. \quad (6)$$

The network manager uses the available energy at central energy source $\hat{Q}_{in}$ to heat up the cold return water (at $T_R$) to $T_S$ as captured by the following equation.

$$T_S = \frac{\hat{Q}_{in}}{MC_p} + T_R. \quad (7)$$

Note that thermal grid managers usually have an operating chart to determine the maximum $T_S$ that can be employed given a certain $T_\infty$. Such considerations impose an upper bound $T_{S,\text{sat}}$ on the temperature to which supply water can be heated to during operation.

III. DEMAND RESPONSE (DR) ARCHITECTURE

In this section, we propose the entire framework for the DR scheme to ensure thermal fairness in the DH network. We first note that the DR signal to be sent to an individual consumer in the network can be realized in different ways. A few possibilities include centrally altering the thermostat set-point of the buildings or by directly controlling the mass flow rates (by controlling relevant valve settings) into the buildings, thus overriding the selfish distributed controller action. In this paper, we assume the latter as our DR signal. We divide the entire time duration of interest i.e. $[0, \tau]$ into successive windows of length $\Delta t$ and perform optimization separately in each time window under steady state of operation. The thermal parameters of the buildings which play a crucial role in the DR optimization are often not known a priori to the central utility and may themselves be dynamically changing on a slow time scale. Thus, these parameters need to be dynamically estimated. Hence, a rolling window approach suits our purpose of considering the dynamic changes to thermal parameters while formulating the DR strategy.

A. Steady state expressions

For practical lossy DH networks, $\epsilon_i \leq 1$, $\forall i \in N_0$ and $\delta > 0$. Detailed analysis as given in our earlier work [14] allows us to express the steady state return temperature of water in the buildings in terms of the ambient temperature $T_\infty$ (which is assumed to be well forecasted), the supply temperature $T_S$, and the indoor zone temperature $T_{z,1}^i$ as,

$$T_{M,R}^i = \beta_i T_{z,1}^i - \alpha_i T_\infty - \gamma_i T_{M,S}^i + \epsilon_i \delta,$$  \quad (8)

where $\beta_i = 2\epsilon_i + \frac{2\epsilon_i}{C_iA_iR_i}$, $\alpha_i = 2\epsilon_i\frac{A_i}{C_iR_i}$ and $\gamma_i = (2\epsilon_i - 1)$. The steady state primary side mass flow rates can be expressed as,

$$\dot{m}_{s,i} = \frac{1}{R_i}(T_{z,1}^i - T_\infty) \quad \frac{C_p(2\epsilon_i T_{M,S}^i - \beta_i T_{z,1}^i + \alpha_i T_\infty - \epsilon_i \delta)}{C_p(2\epsilon_i T_{M,S}^i - \beta_i T_{z,1}^i + \alpha_i T_\infty - \epsilon_i \delta)} \quad (9)$$

Using these above quantities as obtained in (8) and (9) in (7), the steady state energy balance equation for a practical lossy network can be derived as,

$$\hat{Q}_{in} = \sum_{i\in N_0} \frac{1}{R_i}(T_{z,1}^i - T_\infty) - 2 \sum_{i\in N_0} \dot{m}_{s,i}C_pw_i. \quad (10)$$

Note that the second term in equation (10) accounts for the losses in the network.

B. DR optimization framework

The DR architecture is shown in Figure 2. When the central manager performs the DR optimization for a window $k$, given the knowledge of $\hat{Q}_{in}$ and $T_\infty$ in $k$, it uses estimates of $R_i$ and $C_i$ for all buildings. Denote $R_k = \{R_{1,k}, R_{2,k}, \ldots, R_{N,k}\}$ and $C_k = \{C_{1,k}, C_{2,k}, \ldots, C_{N,k}\}$ to be the vector of estimates of
thermal parameters of all buildings available to the central utility for optimization in the window $k$. We assume that the static heat exchanger characteristics $\delta$, $\epsilon_i$ and $U_i A_i$ are available with appreciable accuracy to the central utility. This is a valid assumption as utilities are expected to have the ratings of all the different heat exchangers available under its purview. All steady state expressions as derived in earlier section are computed by the central utility through replacement of $R_i$, $\alpha_i$ and $\beta_i$ by $R_{i,k}$, $\hat{\alpha}_{i,k}$ and $\hat{\beta}_{i,k}$ respectively, wherever applicable. Now that expressions for the estimated steady state return temperatures and mass flow rates of buildings in window $k$ are available for all buildings, the central utility formulates the optimization problem in $k$ as follows:

$$\min_{T_k} J_{fairness},$$

s.t. $2\epsilon_i T_{MS} - \hat{\beta}_{i,k} T_z^a + \hat{\alpha}_{i,k} T_\infty - \epsilon_i \delta \geq 0$, $\forall i$, (11)

$$\lambda_1 T_z^a - \lambda_2 T_\infty - 2 M_{ub} C_p \epsilon_i T_{MS} + M_{ub} C_p \epsilon_i \delta \leq 0$, $\forall i$, (12)

$$T_S \leq T_{ub}^b$$

$$\dot{Q}_{in} = \sum_{i \in N_b} \frac{1}{R_{i,k}} (T_z^a - T_\infty) - 2 \sum_{i \in N_b} \hat{m}_{s,i} C_p w_i.$$ (14)

Here, $J_{fairness}$ is the fairness based objective function (some typical examples of fairness based objectives can be found in [14] while some instances of their application can be found in Section IV), $M_{ub}$ is the upper bound for mass flow rates and $\lambda_1 = \left(\frac{1}{R_{i,k}} + M_{ub} \hat{\beta}_{i,k} C_p\right)$, $\lambda_2 = \left(\frac{1}{R_{i,k}} + M_{ub} \hat{\alpha}_{i,k} C_p\right)$ are parametric constants of the system in window $k$. Constraint (12) and (13) ensures that all primary mass flow rates are lower bounded by 0 and upper bounded by $M_{ub}$ respectively. $T_{ub}^b$ is an appropriately chosen upper bound on the supply water temperature. Constraint (15) is the steady state energy balance equation of the system. $T_k = [T_S^a, T_z^a, T_\infty^a, \ldots T^a_N]$ is the vector of optimization decision variables i.e. steady state supply water temperature and individual steady state building indoor temperatures in $k$. Once the optimal $T_k^a$ is found, the utility can compute the effective DR signals i.e. the optimal primary mass flow rates $\dot{m}_{s,i}$ from $T_k^a$ and (9) using $R_{i,k}$, $\hat{\alpha}_{i,k}$ and $\hat{\beta}_{i,k}$ in place of $R_i$, $\alpha_i$ and $\beta_i$ respectively, wherever needed.

### C. Estimation framework

Once the optimal mass flow rates have been channelized to the primary circuit of all buildings in the window $k$, the central utility (network manager) is assumed to get real time sensor measurements of temperatures from various points in the network. These include time series measurements of supply and return temperatures of all buildings ($T_{MS}^{rec}$ and $T_{MR}^{rec}$ respectively) and the indoor zone temperatures ($T_z^{rec}$) of all buildings. The HVAC power consumption of building $i$ at a measurement instant $j$ within this window $k$ can be computed now directly from the measured sensor values as $Q_{HVAC}^{rec}(j) = \dot{m}_{s,i}^{*}(j) C_p (T_{MS}^{rec}(j) - T_{MR}^{rec}(j))$. Typically these measurements will have some measurement noise associated. Assume sensor measurements are available every $\Delta j$ seconds (say at time stamps $j, j+1, \ldots$ and so on). Now, assuming that $Q_{ai}^{*} = 0$ for all practical purposes, one can use (1) to get a discrete time equivalent of temperature evolution equation for building $i$ as.

$$T_z^{a}(j+1) = a_1 T_\infty(j) + (1-a_1) T_z^{a}(j) + a_2 \dot{Q}_{HVAC}^{rec}(j),$$ (16)

where $a_1 = \frac{\Delta j}{R_i C_i}$ and $a_2 = \frac{\Delta j}{C_i}$. Now, once recorded time series data is available in the window $k$ for $T_\infty$ (usually well forecasted), $T_{MR}^{rec}$ and $Q_{HVAC}^{rec}$, the central utility can employ an optimization to find the optimal $a_1$ and $a_2$ in (16) with an objective of minimizing $e$ where

$$e = ||T_z^{a} - T_z^{a,rec}||_2.$$ (17)

Note that for this optimization, only the most recent time series data i.e. from the window $k$ is used. From the optimal values of $a_1$ and $a_2$ thus obtained, the utility can compute the estimate of $R_i$ and $C_i$ to be used for optimization in time slot $k+1$. The above process can be done in parallel for all buildings to estimate the complete vector $R_{k+1}$ and $C_{k+1}$.

Since we are using a rolling horizon estimator, i.e. we only

\footnote{We use the following convention. Denote a time series vector as $X$ and any singular observation at time $j$ from such series as $X(j)$.}
use time series data available from the latest window under consideration. Thus, the estimator can potentially capture slow varying changes in thermal resistances and capacitances of buildings.

IV. NUMERICAL RESULTS

In this section, we evaluate the proposed DR framework in a test network of 10 small buildings with progressively decreasing insulation parameters and similar heat capacities (same as in [14]). The ambient temperature during the period chosen for DR is assumed to vary in accordance to the temperature of a typically extreme winter day in Lulea, Sweden; an area which caters to a sizable portion of local heating energy needs by district heating. We also assume that the input power available for heating varies with time but is well forecasted. For details about the ambient temperature profile and the input power availability profile, along with other details of the assumed network, the reader is directed to [14]. The preferred set points of all buildings throughout the optimization window is assumed to be 22°C.

![Fig. 3. Variation of indoor zone temperature in buildings without any demand response.](image)

The first experiment we conduct is to see how the network parameters and the individual zone temperatures evolve under conditions of no demand response. In such cases, the individual buildings are assumed to selfishly drive their indoor zone temperature towards their preferred set point by controlling the secondary mass flow rates through a suitable proportional controller. We then compare this with cases where demand response is initiated by the grid manager to effectively induce thermal fairness in the considered network. For better readability, in the remainder of this section, we only report the parameters of 5 of the 10 buildings (buildings numbers 1, 3, 5, 7 and 9) for studying the effects of demand response. When there is no demand response, the indoor temperature profile of different buildings vary as shown in Figure 3. Clearly, buildings do not achieve desired set point since the $Q_{in}$ available during the studied window is insufficient for meeting their energy needs. We also observe that when there is no DR, building 1 is suffering the least discomfort and building 9 is suffering the maximum discomfort. This is owing to the lesser insulation in building 9 as compared to building 1 and greater thermal loss encountered by building 9 due to being located farther down the network from the central energy source.

We assume in the subsequent studies that the central utility has an initial approximate estimate of the thermal parameters. Also, all temperature measurements made from the sensors are assumed to have an additive Gaussian white noise component $\epsilon \sim \mathcal{N}(0, \sigma^2)$ where $\sigma = 0.2$. We assume that re-estimation of thermal parameters and a subsequent optimization for one time slot occurs at a frequency of 1 hour in rolling window manner. We first consider a net utility maximization objective as a fairness metric. Each building $i$ is assumed to have an utility function $u_i(t) = c_i - b_i(T_1^*(t) - T_2^*(t))^2$ where $c_i = 10$ and $b_i = 0.05$ for all buildings.

From Figure 4, we can see how indoor zone temperatures of all buildings are brought closer to one another through DR. The estimator algorithm is also seen to provide better estimates of thermal parameters progressively with time which improves the optimization outcome as seen in Figure 4.

![Fig. 4. Variation of indoor zone temperature in buildings after DR with net utility maximization as the fairness metric.](image)

From Figure 5, we can see how the estimation algorithm manages to find the optimal parameters $a_1$ and $a_2$ (and hence the thermal parameters) from noisy sensor measurements for building 1 with reasonable accuracy to be used in the optimization for the subsequent time slot.

![Fig. 5. Recorded sensor measurements and estimated indoor temperature profile for building 1 during time slot 1.](image)

In Figure 6, we plot the normalized net utilities $U_{i,norm}$ of individual buildings before and after DR where $U_{i,norm} = \frac{U_i}{\max(U_{i,norm-DR})}$ and $U_i = \int_{t=0}^{T} u_i(t) dt$ ($U_i$ is the net utility}
of building \( i \) in \([0, \tau]\). Clearly, we observe that the proposed DR methodology has been able to classify the buildings as (i) DR facilitators i.e. those consumers who give up on a share of their utility hence facilitating the DR, and (ii) DR beneficiaries i.e. those who benefit from DR by having their post-DR utilities improved when compared to their pre-DR counterparts. Overall, we observe that the DR mechanism is able to realize 47% of the available DR potential (maximum total net utility possible minus total net utility without DR).

![Fig. 6. Normalized utilities of individual buildings before and after DR.](image)

We next study the same DR methodology on the same test network under the same conditions with a different fairness metric. In this study, the fairness objective is to minimize the maximum deviation of indoor temperature from its desired set-point across all buildings. We define a new metric to compare the DR performance with the case when there is no DR. Define \( D_i = \int_0^\tau d_i(t)dt \) (where \( d_i(t) = \max(0, T_{i,sp}^c(t) - T_i^c(t)) \)) to be the net discomfort faced by consumers in building \( i \). The normalized net discomfort \( D_i \) i.e. \( D_{i,\text{norm}} \) is defined as \( D_{i,\text{norm}} = \frac{D_i}{\max(D_{i,\text{no-DR}})} \). From Figure 7, we see that the DR mechanism has effectively minimized the dispersion of discomfort among building consumers. As in the earlier case, a classification of consumers into DR facilitators and DR beneficiaries is also evident in this study. Thus, we observe through our numerical studies that the proposed DR scheme can be used effectively to optimize the thermal grid parameters to realize network level fairness objectives.

![Fig. 7. Normalized net discomfort of individual buildings before and after DR.](image)

V. CONCLUSION

In this paper, we propose a DR framework for a DHC network (also known as thermal grids) in which the primary side mass flow rates of water to different buildings are centrally optimized by the network manager (central utility) to realize targeted network level fairness objectives. In devising the mechanism, we addressed the network manager’s lack of accurate knowledge of thermal parameters of buildings by designing a suitable estimator which dynamically estimates the required parameters with reasonable accuracy. Possible extensions to this work includes (but not limited to) designing an consumer level incentive mechanism for implementing this DR scheme in practice. Also, the effect of network topology on the DR mechanism can be studied.

REFERENCES