



A Review of District Heating Systems: Modeling and Optimization

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The ever-increasing demand for heating in different sectors, along with more preventative regulations on greenhouse emissions, has forced different countries to seek new alternatives to heat buildings such as district heating system (DHS). Although rudiments of DHSs can be observed over the centuries, it was not widely implemented until last two decades when the DHS became a strategy to design more energy-efficient way of heating the buildings. This paper suggests a new approach in categorizing DHSs based on their geographical location, scale, heat density, and end-user demand. Furthermore, this paper reviews system and component modeling approaches with a focus on DHS load prediction. Main limitations of the existing methods are also addressed and discussed with a comprehensive review of the recent studies. Finally, the state of the art in optimization of the different DHSs has been reviewed and categorized based on their objective functions and the techniques used for solving optimization problems (deterministic and heuristic).

OPEN ACCESS

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Specialty section:

This article was submitted to
Sustainable Design and Construction,
a section of the journal
Frontiers in Built Environment

Received: 29 June 2016

Accepted: 13 September 2016

Published: 04 October 2016

Citation:

Talebi B, Mirzaei PA, Bastani A and
Haghighat F (2016) A Review of
District Heating Systems: Modeling
and Optimization.
Front. Built Environ. 2:22.
doi: 10.3389/fbuil.2016.00022

Keywords: district, heating, modeling, optimization, energy

INTRODUCTION

The global population will exceed 9.7 billion by 2050 (United Nations, 2013), which will lead to approximately 70% increase in the number of households from 1.9 billion in 2010 to 3.2 billion in 2050 (I.E. Agency, 2012). Residential and commercial buildings account for about 40% and 26%, respectively, of total energy consumption in U.S. and European households (Mertens, 2013; I.E. Agency, 2012). About 38% and 36% of U.S. and EU carbon dioxide (CO₂) emissions are also associated with these buildings. Moreover, several unwanted side effects, such as urban heat island, are associated with the drastic increase in urbanization (Mirzaei, 2015; Mirzaei et al., 2015). Thus, these statistics emphasize the necessity of a global objective to reduce the CO₂ emission by half by 2050, which is described as the goal of the Energy Technology Perspectives 2012 roadmap (EIA, 2011). This calls for increased efforts and market uptake from the building sector to reach the ambitious goal of net-zero energy buildings (NZEB) by 2050 given the 50% rise in energy demand predicted by the current consumption trajectory. Another example is European Union obligation in 9% reduction in energy use by 2016 based on 2006/32/EC directive (European Parliament, 2006). The European countries are also committed to increase the share of renewable energy sources to 20% by 2020 (P.H.A.F.S. Committee on Environment, 2011).

Different strategies in energy production, conversion, and user-side demand have been proposed to conserve energy in the building sector, i.e., increasing the energy efficiency of buildings with refurbishment technologies such as thermal insulation, double and triple glazing, solar shadings, cavity wall, reflective coating windows, efficiency enhancement, the functionality performance of HVAC equipment, integrating renewable strategies such as BIPV and solar collectors, utilizing natural ventilation. In addition to these technologies, one of the viable solutions is to improve the energy efficiency in buildings, which can be accomplished by using district heating system (DHS)

(International District Energy Association, 2014; <http://www.districtenergy.org/what-is-district-energy>).

Traditional DHSs are generally used for residential space heating and domestic hot water, which are accounting for the largest share of energy consumption in buildings (International District Energy Association, 2014; <http://www.districtenergy.org/what-is-district-energy>). Other advantages of DH are known as the improvement of resource and energy management and also reduction in the user-side costs, including operation, maintenance, and safety expenses (Rezaie and Rosen, 2012). Moreover, flexibility and safety in selection of the energy source such as biomass and geothermal energy instead of fossil fuels, which dominates the current heat market, is another attractive option of the DHSs (Hepbasli, 2010; Akhtari et al., 2014).

Despite the well-known advantages of DHS, its market share around the world is still very low while only about 6000 DHSs exist in European Union with the market share of about 13% (Figure 1). Besides many social, economic, and technological issues revolving around worldwide implementation of DHSs, the predominant reason for neglecting such systems is the lack of suitable tools to design, analyze, and optimize them (Connolly et al., 2014).

Apart from such issues, one of the major limitations of DHS is lower thermal comfort, especially in older DHSs where occupants have very little control over the water temperature (International District Energy Association, 2014; <http://www.districtenergy.org/what-is-district-energy>). In denser urban regions, which expanding the DHS distribution network should follow the rules of the municipality, existing infrastructure, such as roads, water/sewage distribution networks, and city layout in some cases, are the common barriers against the optimal expansion of DHSs.

The discussed advantages and limitation in DHSs has persuaded the communities to move toward the implementation of

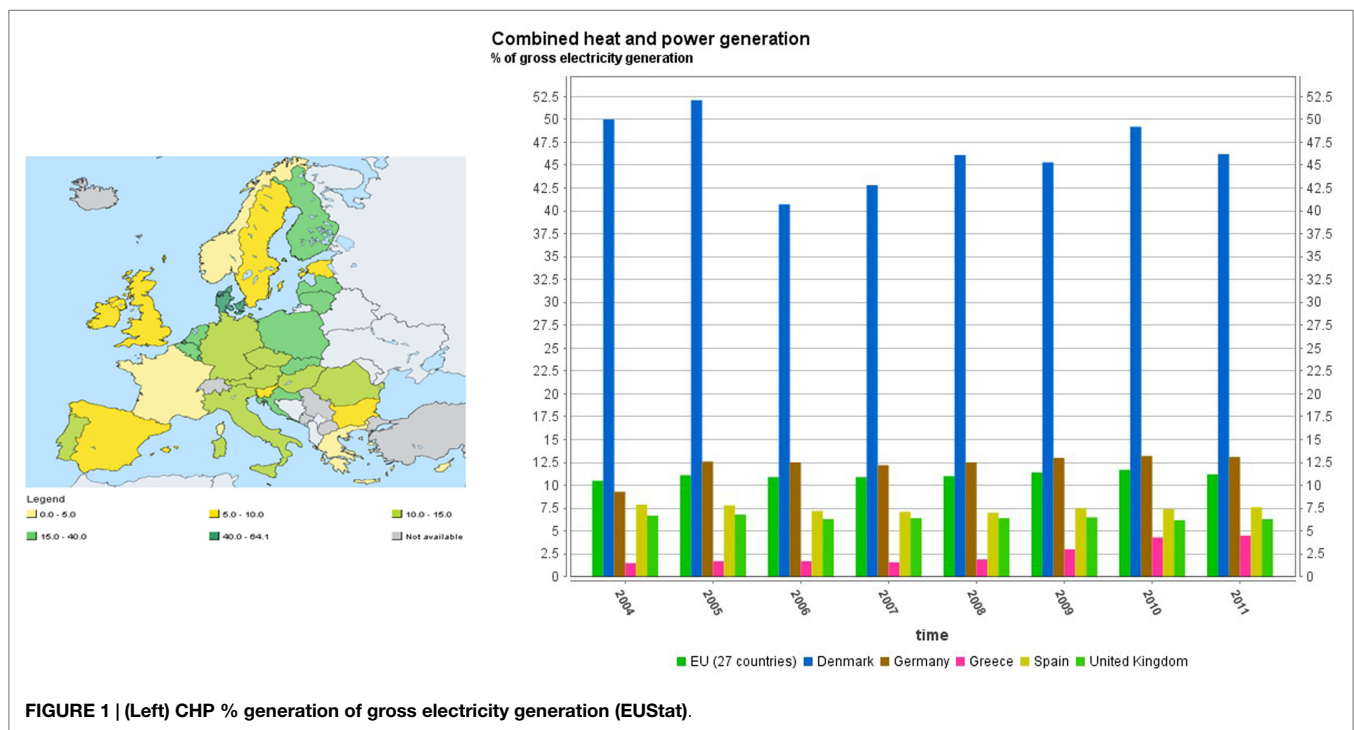
novel ideas and strategies in energy sharing and management of DHSs. The new strategies are mainly focused on combining renewable energy, use of storage technologies, and establishing a linkage between heating and electricity systems to significantly reduce the dependency on the fossil fuel resources (International District Energy Association, 2014; <http://www.districtenergy.org/what-is-district-energy>). One of the major challenges toward the design of such systems is associated with lack of available tools, which can effectively model and optimize DHSs.

To shed more light on the recent achievements in modeling and optimization of DHSs, this paper aims to summarize the current state of the art. Thus, various definitions of DHS are first provided followed by the molding approaches utilized to investigate the performance of these systems. Eventually, modeling and optimization of DHS studies based on different climates, scales, energy sources, and implemented tools are further summarized in this paper.

COMPLEXITY LEVEL OF DISTRICT HEATING SYSTEMS

In general, a DHS consists of a heat source, a network of users, and a distribution network. The complexity of a DHS varies in accordance with various parameters as stated below (Sakawa et al., 2002; Weber et al., 2007):

- (a) *Number of utilized technologies*: one of the complexities of design and optimization of the DHSs is the number of technologies available to be utilized in addition to the type of the heat source system. For example, in DHSs with geothermal energy source, the system could operate with the organic fluid instead of water (Weber et al., 2007), while in case of having heat sink close to the DHS, the heat pump is more favorable.



Moreover, a combination of sources can be used in DHS, while other renewable source of energies can be integrated to the system (Sakawa et al., 2002; Weber et al., 2007).

- (b) *Number of end-users*: one of the main concerns in designing a district heating is the number and variety of the users connected to the system. A DHS located in a municipal area serves a variety of residential, commercial, and industrial buildings with different demand levels (Pirouti et al., 2013).
- (c) *Temporal profile*: different types of users connected to a system demand their own operating temperature and profiles (Weber et al., 2007). For example, the heat demand profile for industrial users will be effected less by seasonal changes during a year, meaning that their required end-use temperature is higher compared with residential users (Buoro et al., 2014).
- (d) *Spatial concerns*: in addition to the coordinate of all users, the layout of a city, in which a DHS is planned, plays a key role in design of distribution network. For example, interception with municipal infrastructures should be avoided when a network is designed. Other factors such as soil quality, topology of the region, and type of the users could similarly affect the design of a DHS (Weber et al., 2007; Ben Hassine and Eicker, 2013).

CLASSIFICATION OF DISTRICT HEATING SYSTEMS

In general, a DHS can be categorized based on five main parameters including geographical conditions, scale of the DHS, heat

density of the DHS, the level of end-user demands, and type of heat sources.

Geographical Conditions

Geographical considerations, namely climatic conditions and energy source accessibility, will impact the overall design of a DHS. In particular, a DHS close to Northern latitudes with a colder climate requires higher rate of heat transfer per unit area compared to the DHS closer to the equatorial line with a warmer climate for similar types of buildings (Dalla Rosa and Christensen, 2011). This higher amount of heat transfer in DHSs can be reached either by increasing the mass flow rate of the fluid or by increasing the operational temperature of the system, which consequently increases the distribution heat loss of the system due to the higher operational fluid temperature (Hassine and Eicker, 2011).

Energy sources accessibility is a function of geographical and geological variation and, therefore, impacts the design considerations of a DHS. Investigating the distribution of different energy resources for different geographical locations addresses the accessibility of at least one of the main sources of renewable energy at any region. For example, comparison of the solar (Huld and Pinedo-Pascua, 2012) and wind map of Europe (see text footnote 1) shows that region with lower solar intensity have higher wind speeds and vice versa (Figure 2). Specifically, Scandinavian region has one of the lowest solar intensities while it is exposed to the highest wind speed in Europe.

Scale

Scale of a DHS plays a significant role in performance of such systems as the influential parameter in design stage varies in accordance with the scale. From the spatial point of view, DHS can be designed as a small, medium, or large system (Figure 3).

¹European Wind Atlas. Copyright © 1989 by Risø National Laboratory, Roskilde, Denmark. http://www.wasp.dk/dataandtools#wind-atlas_european-wind-atlas

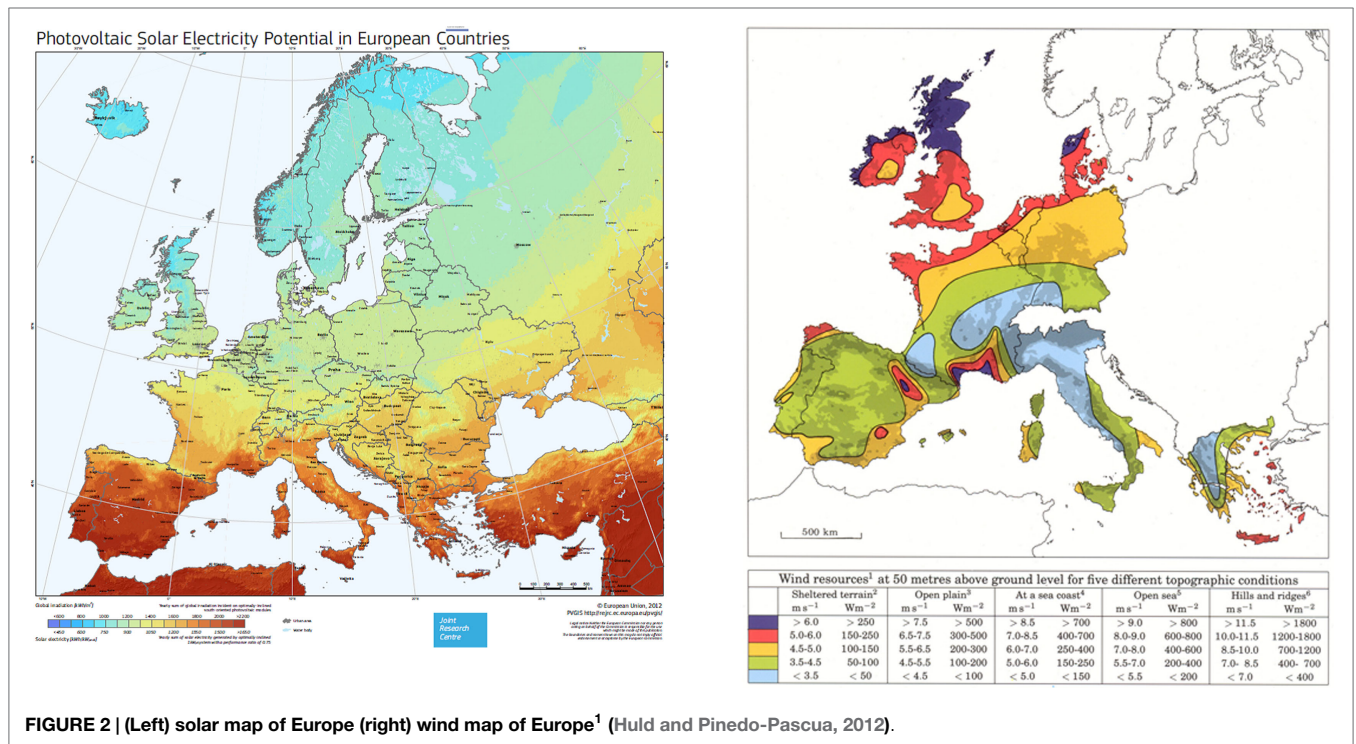
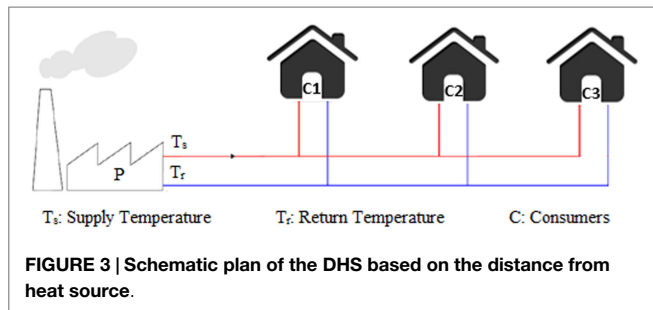


FIGURE 2 | (Left) solar map of Europe (right) wind map of Europe¹ (Huld and Pinedo-Pascua, 2012).



Small-scale DHS is referred to a network of users in which the distance from the heat source is in the order of magnitude of less than few hundreds of meter (Weber et al., 2007). In fact, the associated temperature and pressure drops are relatively low due to the short length of the pipelines in the distribution system (Hurtig, 2010). DHSs in the level of multi-residential buildings are more likely known as small systems with a relatively low temperature drop.

The distance between the heat source and the users is mainly assumed to be from 200 to 300 m in the medium-scale DHS (Weber et al., 2007; Dalla Rosa and Christensen, 2011; Ancona et al., 2014). In general, these systems are formed as a close-loop network of buildings linked together with a piping system. Similar to the small-scale DHSs, pressure drop is a significant element in design of such systems, whereas for older generation or higher operating fluid temperature systems, the heat loss is substantial and should be considered at the design stage (Hassine and Eicker, 2011; Nuytten et al., 2013).

Large-scale DHS, mostly known as community size DHSs, consists of many users and a longer pipeline network compared with the latter groups. Due to longer length of the pipes in distribution network, the heat loss is considerably significant and accounts for up to 15% of the total energy delivered by the system (Hassine and Eicker, 2011; Xing et al., 2012).

Heat Density

Linear heating density of a network (LHD) is defined based on the ratio of its total annual heating demand over trench length (Reidhav and Werner, 2008):

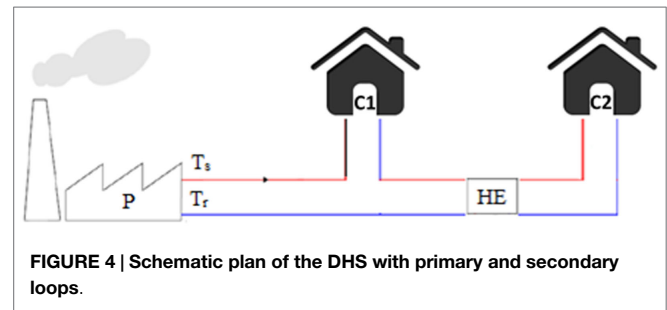
$$\text{LHD} = \frac{Q_{\text{total}}}{L} \quad (1)$$

where Q_{total} is the total annual heating demand of the DHS, and L is the total trench length of the distribution network.

Based on this definition, higher LHD means higher heat density of the network or users with a higher annual demand. In systems with higher heat density, the importance of the heat loss is less significant (Nuytten et al., 2013), and thus the system is designed only based on the hydraulic equilibrium. The economic and environmental threshold for the LHD of different networks are varied from 1 MWh/m for DHSs with biomass heat source to 0.2 MWh/m for combined heat and power (CHP)-based systems (Reidhav and Werner, 2008; Nuytten et al., 2013).

End-User Demand

Residential buildings utilize lower end-use temperatures for heating while industrial users require higher fluid temperatures. This



means that the demand level of users in a network results in different arrangement of the DHS (Buoro et al., 2014). One arrangement is to design a network based on the maximum demanded temperature (Pirouti et al., 2013), while another option is to use a multi-loop network with different operational temperatures associated with each of them. Multi-loop networks further interact with each other through sets of heat exchangers (Figure 4). This implies that the main loop operates with the maximum temperature while secondary loops operate at lower temperatures in order to satisfy the temperature requirements of all users (Hassine and Eicker, 2011; Ben Hassine and Eicker, 2013).

Heat Source Type

In general, heat sources are categorized as permanent and non-permanent types. In the permanent heat sources, the heat generation continuously exceeds the heat demand of the network where in the non-permanent sources the generation profile fluctuates during the time. In the latter scenarios, the generation mainly does not match with the user demand profile, and therefore another energy source is mostly integrated to meet the peak demand of the system.

Combined heat and power, geothermal, and biomass sources are known as permanent source (Hlebnikov and Siirde, 2009; Noussan et al., 2014; Sartor et al., 2014). On the other hand, convertible renewable sources into thermal energy such as wind and solar energy with high rate of fluctuations are categorized as non-permanent sources. Moreover, heat storage systems can be integrated into DHSs to store the surplus of generated heat at their off-peak time to be later utilized at the peak time of the DHS (Avila-Marin et al., 2013; Nuytten et al., 2013).

COMPONENT MODELING OF DISTRICT HEATING SYSTEM

Accurate modeling and design of each DHS's component plays an important role in its efficacy and efficiency. This section investigates various techniques employed to model DHS's components.

Heat Source

In general, heat sources in DHSs are modeled based on their efficiency and heat generation output. A minimum efficiency index has been defined depending on the type of the heat source. For example, the primary energy saving index (PES) has been

defined to evaluate the efficiency of a CHP heat source (Noussan et al., 2014):

$$PES = \left(1 - \frac{1}{\frac{CHP H\eta}{Ref H\eta} + \frac{CHP E\eta}{Ref E\eta}} \right) \times 100\% \quad (2)$$

where CHP $H\eta$ is the heat efficiency in cogeneration production, Ref $H\eta$ is the efficiency in separated heat generation, CHP $E\eta$ is the electricity efficiency in cogeneration production, and Ref $E\eta$ is the efficiency in separated electricity generation.

The minimum value of the PES for CHP heat sources with the nominal size of smaller than 1 MW should be a positive value while this value is more than 0.1 for sources above 1 MW (Noussan et al., 2014). Same types of indices have been defined for other type of heat sources (Hepbasli, 2005).

End-User Profile

Accurate prediction of the energy demand profile of users in smaller time interval such as hourly basis can affect the efficiency of a network as well as its optimization procedure (Ortiga et al., 2007). The DHS modeling of the users' network consists of two levels: understanding of the heating demand profiles of the users in order to define the total load required for the network and calculation of a heat exchanger for each user.

Since building heterogeneity in each district system is elevated, particularly in the urban setting, and each building has its own properties and corresponding demand profile, determining the model which could predict the demand profile of the entire district with acceptable accuracy, is essential. In general, there are different methods suggested to model and predict this demand. Many of these methods predict the energy demand of a building in terms of its maximum energy demand, while others predict the actual profile of the building in smaller intervals such as an hourly basis.

Regardless of the method used, the heating demand profile of each user consists of three major parts, including physical and environmental characteristics of a building (i.e., R -value, infiltration rate, ambient air temperature, solar radiation, and humidity), human-related factors or social behavior of the occupants, and random factors that account for uncertainties. Different techniques have been suggested in the literature in order to predict the demand profile of the users considering one or all of the above factors including historical approaches (Dotzauer, 2002; Ortiga et al., 2007), deterministic, and times series predictive methods (Eriksson, 2012).

Historical Methods

These methods use historical data obtained from both demand and supply sides to model the demand profile of the system.

Heating Degree Day

Heat loss in buildings is proportional to the difference between indoor and outdoor ambient temperature. This concept is used in the development of the Heating Degree Day method (HDD) (Day, 2006):

$$\text{Heat Loss (kW)} = \text{Overall Heat Loss Coefficient (kW.K}^{-1}) \times \text{HDD (K)} \quad (3)$$

Here, the overall heat loss coefficient is determined based on the infiltration rate and the summation of the UA value for all different envelope assemblies of the building. The infiltration rate can be defined either as an average or hourly rate (Day, 2006).

Online and free historical weather data are mainly assumed as reliable sources to obtain the HDD method (Verda et al., 2012; Pirouti et al., 2013).^{2,3} This method is widely used for modeling of small buildings in which the main source of heat loss is unclear in their envelope. Al-Homoud (2001) compares this method with another historical method known as the Bin method. Unlike the degree day method, the bin method is mainly used for larger scale buildings in which the internal load generation has a higher effect, rendering the degree day method unfeasible. In both cases, the main concern in modeling is the outdoor air condition of the buildings and the average envelope thermal resistance. The fact that factors such as the social behavior of occupants and the thermal mass of the buildings have not been taken into account result in predominantly poorly accurate findings (Dotzauer, 2002). Furthermore, the low frequency of available data results in inaccurate outcomes.

Energy Use Intensity and Load Factor

Energy use intensity (EUI) and load factor (LF) is another technique to estimate the users demand profile, whereby the historical supply data are provided. EUI is the rate of energy use per unit area (Sharp, 1996), and LF is the ratio of energy consumption over the maximum possible energy generation of the supply side (Dalla Rosa and Christensen, 2011; Dalla Rosa et al., 2012):

$$LF = \text{Consumption (kWh)}/\text{Peak Demand (kW)} \times \text{Time (h)} \quad (4)$$

Knowing the EUI and LF of different users⁴ results in calculation of the total energy and peak heating demand required for each consumer. The supply energy demand calculates the annual average LF per area of different users. Mainly, the values are accessible based on region or reference archetype (see text footnotes 3 and 4). Barnaby and Spitler (2005) used this method for load prediction based on different users' sector of the DHS and added them together to predict the users' heating demand profile. One of the main problems with this method is associated with non-existence of separated factors for ambient conditions.

Measurements

Measurement campaigns can provide reliable inputs to be inserted as the end-user demand profile of DHS (Sanaei and Nakata, 2012; Nuytten et al., 2013; Wang et al., 2013; Noussan et al., 2014). Achieving a high frequency dataset, however, is not always a feasible option due to the extensive cost of the equipment and time-consuming procedure.

²Degree Days Weather Data for Energy Professionals. Available at: <http://www.degreeedays.net/>

³Energy Use Data Handbook. (2013). Available at: <http://oee.nrcan.gc.ca/publications/statistics/handbook2010/handbook2013.pdf>

⁴Commercial & institutional consumption of energy survey summary. (2008). Available from: <http://oee.nrcan.gc.ca/publications/statistics/cices08/pdf/cices08.pdf>

Archetype Building

Another type of the widely used historical methods is prototype or archetype buildings. In this method, buildings with a same occupancy type are divided into subcategories, while a reference building is defined for each building. The demand profile of other buildings located in each category is later defined based on the reference building with some adjustment. The number of building categories used in this method and the number of adjustments required for modeling the demand profiles are the key parameters of the prototype method. The most commonly utilized technique is the regression method. Lara et al. (2015) used the linear regression method in order to define the useful parameter that can be employed as an input data for modeling of school buildings, whereas Filippin et al. (2013) used a multivariate regression method in evaluating the heating demand profile of a residential sector.

Deterministic Methods

Deterministic methods, also referred as simulation-based models, use the mathematical representation of the physical behavior of the buildings. Based on the volume of the used information, deterministic methods can be categorized into two major subdivisions, such as complex or software-based simulation models, which use different simulation software that takes into account all the different parameters affecting the demand profile of a building and simplified models, which basically simplify the level of the calculations taken into the account.

Complex Models

Energy simulation software, such as Energy Plus (Crawley et al., 2001) and TRNSYS (University of Wisconsin—Madison, Solar Energy Laboratory and Klein, 1979), is broadly used for modeling various type of buildings. Although they yield highly accurate demand profiles, the main disadvantage of these models is their dependency on data quantity and high computational cost for modeling each building (Ortiga et al., 2007; de Guadalfajara et al., 2012; Guadalfajara et al., 2014). For small-scale systems consisting of a limited number of buildings, using the comprehensive method can increase the accuracy of the simulation. Nonetheless, providing the data and time required for modeling of many buildings in a city-wide scale is very extensive. The example of complex modeling is a work by Zhang et al. (2015, 2014) where a comprehensive method was utilized to model the demand profile of 95,817 buildings in Westminster, UK.

Simplified Models

Simplified methods are adapted when the adaption of the comprehensive method is relatively extensive for a large-scale community. These methods simplify physical characteristics of the buildings in order to predict their demand profile. For example, Kim et al. (2014) considered the parameters including shape, orientation, and occupancy type in the modeling of the end-users' profile. They used the average energy required per square meter of a dwelling area of a building based on its monthly/yearly outdoor design temperature. In order to take into account the shape and orientation of the building, new sets of coefficients were introduced: (1) the ratio of the outdoor surface to volume of the building (the shape factor) and (2) the orientation relative to the south

(orientation factor) (de Guadalfajara et al., 2012). Wang and Xu (2006) used a simplified physical method to predict the demand profile load within which they also included the effect of thermal mass on load prediction by means of a genetic algorithm. Results obtained from their simulations illustrate a good correlation with actual data for a residential building, which has a lower internal heat gain density. Inversely, this method is unsuitable for larger buildings with higher internal heat gain density.

Predictive Time-Series Methods

The predictive time-series methods rely on the mathematical curve fitting relations in order to predict the demand profile of the users.

Predictive Models

Different predictive models have been suggested for modeling the demand profile, including classical approaches [i.e., time-series ARMA models, regression (Lei and Hu, 2009; Yun and Steemers, 2011; Guadalfajara et al., 2014), Kalman filter] and artificial intelligence (AI) methods [i.e., artificial neural network algorithms (ANN) (Hippert et al., 2001) and fuzzy neural network (FNN)] (Gross and Galiana, 1987).

ARMA Type. ARMA time-series predict the profile of the end-user by implementation of a linear combination between the previous value of the demand along with previous and current values of the noise (Gross and Galiana, 1987):

$$z(t) = Y_p(t) + Y(t) \quad (5)$$

where $Y_p(t)$ represents the day and the normal weather condition for the design day, and $Y(t)$ indicates the effect of deviation from the normal weather pattern.

With slight difference from the general form, different kinds of ARMA-type models can be developed, e.g., Box-Jenkins (Tang et al., 1991), time series (Amjady, 2001), and ARIMA (Lee and Ko, 2011).

Kalman Filter. Similar to other predictive methods, this technique estimates the value of the variables for future time steps ($t + \Delta t$) based on the values of the variables at its current time step (t). In order to make the best estimation, Kalman filter determine the best variable set, which minimizes the source function using the residual sequence method. In each step, the Kalman filter will check the difference between the measurements and the model output and chose the variable set to minimize the difference. Since the deviation from the measurement can be positive or negative, two different sets of residual sequences could be assumed for the system, such as residual for the hot side and residual for the cold side of the profile (Palsson, 1993).

Artificial Intelligence

Using predictive methods, such as artificial intelligence, is another approach to predict the demand profiles of the building. The most common artificial intelligence methods used in the field of load prediction are ANN, FNN, and Support Vector Machine (SVM). The ANN has been widely used in research for predicting

the load particularly in forecasting the electricity consumption of buildings (Zhang et al., 1998). In most of the cases, ANN shows higher prediction performance compared with other simulation-based methods. This higher accuracy with the ANN method is usually due to its higher adaptability, as it considers the social parameters in load prediction due to the integration of real case data into the system training (Zhang et al., 1998; Hippert et al., 2001). Despite the high accuracy of the predictive methods, their main drawbacks are the over-fitting problem as well as the data requirements for the training purposes. Providing accurate, comprehensive archives of data for ANN is one of the main drawbacks of this method. In cases where the data archive used for training the system is small, using the SVM methods (Chen et al., 2004) shows a better performance. However, only a scarce number of studies were conducted using SVM in the last few years; hence, the information regarding the utilization of this model is limited.

Limitations of the Current Models

The main limitations of the methods have been used in prediction of the demand profile of the DHS could be addressed as below:

- Feasibility of expanding one model to the entire district level: the first limitation of the presented methods is related to the limitation of these models in prediction of the total energy consumption of the entire district. Especially, in case of a larger district system that the heterogeneity of the buildings is elevated, this problem becomes more amplified. For instance, HDD should be only used for prediction of the small residential

buildings while the Bin method is more suitable for larger buildings with much higher internal heat generation density. As a result, an archetype method with a combination of these methods should be used to predict the total energy load of the entire network.

- Type of prediction: another limitation of the presented works is the type of prediction. Most of the presented methods have been adapted to predict the total energy consumption. Even though at the design stage, DHSs are designed based on the total energy consumption and the maximum peak demand of the system, detail profile of the network is further required in order to improve the efficiency of the system and enhancing the energy distribution management. **Table 1** summarizes different prediction methods that have been used to predict the consumption load of DHSs.

As illustrated in **Table 1** most of the works that have been done only focused on the total energy consumption of the networks and not the detail profile.

- Accuracy: accuracy of the prediction is the next limitation of the previous models. In case of load prediction for district systems, two different types of errors could be defined; the first type is the error associated with the entire district model, while the second one is associated with the modeling at the building level. As illustrated in **Table 2** the simulation error is mainly much lower at the district level in comparison with the building level 1, which is mainly related to behavior of the users.
- Computational time: the computational time of the stock modeling is one of the major limitations of the current DHS models.

TABLE 1 | Summary of the method has been used for load prediction in DHS and type of building stocks.

Reference	Country	Method	Simulation		
			Scaling	Building type	Output
Shimoda et al. (2004)	Japan	Archetype/survey	No/archetype	Residential	Total EUI
Heiple and Sailor (2008)	USA	eQuest/comprehensive modeling/archetype	Area weighted	Mixed	Hourly/total consumption
Dall et al. (2012)	Italy	Regression analysis of measured data	Area weighted	Residential	Total consumption
Tuominen et al. (2014)	Finland	Archetype/linear development using REMA	No/archetype	Mixed	Total consumption
Caputo et al. (2013)	Italy	Archetype/comprehensive modeling	Area weighted	Mixed	Total consumption
Filogamo et al. (2014)	Italy	Simplified/equivalent resistance	Area weighted	Residential	Total consumption
Theodoridou et al. (2011)	Greece	Archetype/comprehensive modeling	Area weighted	Residential	Hourly/total consumption
Eicker (2004)	Germany	Simplified/equivalent resistance/DD	Bldg. by Bldg.	Mixed	Total consumption
Fonseca and Schlueter (2015)		Simplified/HDD adjusted/archetype	Area weighted	Residential	Total consumption

TABLE 2 | Summary of the accuracy level of the previous works.

Prediction error for district			Prediction error for individual buildings		
Reference	Country	Error (%)	Reference	Country	Error (%)
Shimoda et al. (2004)	Japan	18	Sehrawat and Kensek (2014)	USA	11–23
Heiple and Sailor (2008)	USA	10–13	Theodoridou et al. (2011)	Greece	12–55
Galante and Torri (2012)	Italy	10	Nouvel et al. (2013)	Germany	5–50
Caputo et al. (2013)	Italy	4	Nouvel et al. (2013)	Germany	18–31
Filogamo et al. (2014)	Italy	8	Koene et al. (2014)	Germany	1–60
Nouvel et al. (2013)	Germany	21	Orehounig et al. (2014)	Switzerland	6–88
Nouvel et al. (2013)	Germany	7	Fonseca and Schlueter (2015)	Switzerland	8–99
Orehounig et al. (2014)	Switzerland	8			
Fonseca and Schlueter (2015)	Switzerland	9–66			

Energy Distribution Network

A distribution network of a DHS is mainly designed in accordance with the scale of the system, geographical considerations, type of the users, and utilized heat generations sources. Besides the role of the distribution network in linking the generation side with the demand side of the cycle and defining the inter communication between different components of the system, the distribution network has an effect on the energy consumption of the system as well. In general, the total energy required to be fed to the system is equal to:

$$Q = Q_{\text{loss}} + \int_1^n Q_i \quad (6)$$

where Q is the total energy consumption of the DHS, Q_i is the demand profile of each user, and Q_{loss} is the heat loss of the system. Since most distribution networks work within a specific temperature range, the heat loss from the system could be considered as a function of the size of the network and not a function of time. As a result, the total energy requirement of the system is equal to the summation of the profiles of different users in addition to the heat loss per network length. Since the DHS is type of the hydronic system, the modeling technique to design the distribution system can be either based on hydraulic or thermal equilibrium.

Hydraulic Equilibrium

The distribution system in the DHS works based on the transferring of heat through a heated fluid, and therefore, it should be designed based on the requirements of the hydraulic system regardless of the flow rate and energy level of the fluid.

Mass Flow Balance

The mass flow balance could be written for each point of the system as follows (Ben Hassine and Eicker, 2013; Kuosa et al., 2014):

$$\sum_{\text{in}} Q_{\text{in}} - \sum_{\text{out}} Q_{\text{out}} - \sum_{\text{user}} Q_{\text{user}} = 0 \quad (7)$$

where Q_{in} is the mass flow rate enter the point, Q_{out} is the mass flow rate exit the point, and Q_{user} is the mass flow rate required by the utility. Depending on the type of the system, such as an open or closed loop, Q_{user} could be considered as 0. It is important to note that the system and network are assumed to be leak free without any loss of the fluid mass.

Energy Balance

In the mass flow balance techniques, the energy balance could be written between any two points in the system as below (Ancona et al., 2014):

$$\Delta H_{ij} - (H_i - H_j) = 0 \quad (8)$$

where ΔH_{ij} represents the energy loss between points i and j ; H_i and H_j are, respectively, the energy content of the fluid at points i and j . Considering the DHS as a closed system and without any loss in the liquid mass, the energy loss in the system could be written as a correlation to the pressure loss in the system represented in two different ways:

$$\Delta H = f \cdot \frac{L}{D} \cdot \rho \cdot \frac{v^2}{2} \quad \text{Distribution Pressure Drop} \quad (9)$$

$$\Delta H = \beta \cdot \rho \cdot \frac{v^2}{2} \quad \text{Concentrated Pressure Drop} \quad (10)$$

In the distribution pressure loss, the friction loss due to viscous effect, generated by the pipe surface, is the governing parameter. The hydraulic diameter of the pipe, mass flow rate of the system, and roughness of the pipe surface are the parameters affecting the distribution pressure loss of the system (Kuosu et al., 2014). Additionally, in concentrated pressure loss, head loss due to fittings and changes in diameter of the pipe are taken into the account (Ancona et al., 2014).

Thermal Equilibrium

Thermal equilibrium can be represented as either a steady-state or dynamic equation. DHS with operational temperature lower than 70°C or with low heat propagation (well insulated) can be represented as a steady-state system. Inversely, DHS operating with higher temperatures than 110°C or with high heat propagation can be considered as dynamic system (Madsen et al., 1994; Lund et al., 2014). The thermal model could be written based on two major sources of the temperature drop in the system, including temperature drop across the users and due to the heat loss in the system. The temperature drop across the users can be modeled based on a simple convection heat transfer equation (Dahm, 1999; Wang et al., 2013):

$$Q = U \cdot \Delta T \quad (11)$$

where Q is the amount of the energy required by the system, U is the heat transfer coefficient, and ΔT is the temperature drop across the users.

On the other side, the temperature drop due to heat loss in the system occurs in both longitudinal and radial directions. Longitudinal heat loss is along the system between different locations, whereas radial heat loss occurs in the surrounding environment. Both types of the heat transfer in the system could simply be modeled by using the enthalpy balance between any two points (Hassine and Eicker, 2011; Kuosa et al., 2013):

$$\frac{\partial(mh)}{\partial t} = \sum_{\text{in}} h_{\text{in}} - \sum_{\text{out}} h_{\text{out}} - \sum_{\text{loss}} h_{\text{loss}} \quad (12)$$

$$\frac{\partial(mh)}{\partial t} = \dot{Q}_c(x) - \dot{Q}_c(x + dx) - d\dot{Q}_1 \quad (13)$$

where \dot{Q}_c is the convective heat flow, $d\dot{Q}_1$ is the radial heat flow and could be expressed as below:

$$d\dot{Q}_1 = k \cdot dx \cdot (T - T_{\text{earth}}) \quad (14)$$

$$\dot{Q}_c(x) = q_{\text{mx}} \cdot T_x \cdot C_p \quad (15)$$

where k is the radial heat transmission coefficient and q_m is the flow rate. By replacing the $d\dot{Q}_1$ and $\dot{Q}_c(x)$ in the Eq. 12, the temperature at any point can be calculated as follows (Figure 5):

$$T_i^{n+1} = T_i^n + \Delta t / m_i \cdot C_p \cdot (q_{m_{i-1}} \cdot C_p \cdot T_{i-1}^n - q_{m_i} \cdot C_p \cdot T_i^n - d\dot{Q}_1) \quad (16)$$

where C_p is heat capacity, T^n is the temperature, Δt is the time step, and m_i is the mass of the water.

Based on the definition of the $d\dot{Q}_1$, one of the main factors influencing the amount of heat loss is the earth's temperature. In

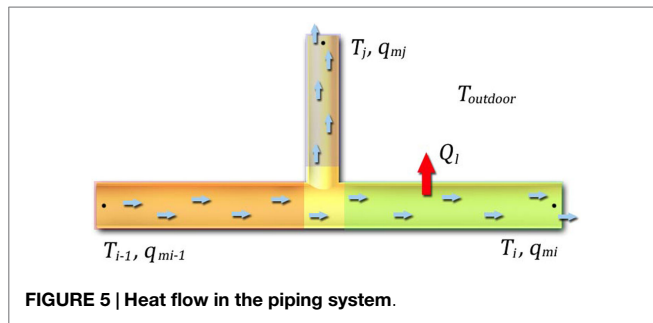


FIGURE 5 | Heat flow in the piping system.

systems with a higher operating temperature, higher differences in temperature could result in higher amounts of the heat loss in the system. Similarly, increased heat losses in a system could result in increased surrounding temperatures over time, and consequently decreasing the heat loss over time.

HOLISTIC MODELING OF DISTRICT HEATING SYSTEM

Physical and black box models are the approaches conducted in holistic modeling of the DHS (Palsson, 2000). The network has been considered as a whole package in the black box models where individual design of the components is disregarded. The whole system is then modeled by techniques such as the transfer function or ANN (Yabanova and Keçebas, 2013). One the other hand, in physical models, each component of the DHS has been designed separately and as a set of equations describing the flow and pressure losses of that element. Arsene et al. (2004) categorized the physical modeling as the link flow (Q), the loop corrective flow (ΔQ), the nodal heads (H), and finally the mixed node-loop approaches.

Due to a high number of the elements that need to be taken into consideration, solving such a system can be computationally expensive. Therefore, numerical approaches have been widely developed for solving the system of equations of the hydraulic distribution networks. Some of these approaches are categorized by Arsene as:

- Numerical minimization method, finding the minimum value of the non-linear function subjected to linear constrained;
- Hardy-Cross method, solving the system of non-linear equations (Chenoweth and Crawford, 1974);
- Newton-Raphson method, solving the system of non-linear equations (Donachie, 1974);
- Linear theory method, solving the system of non-linear equations (Collins and Johnson, 1975).

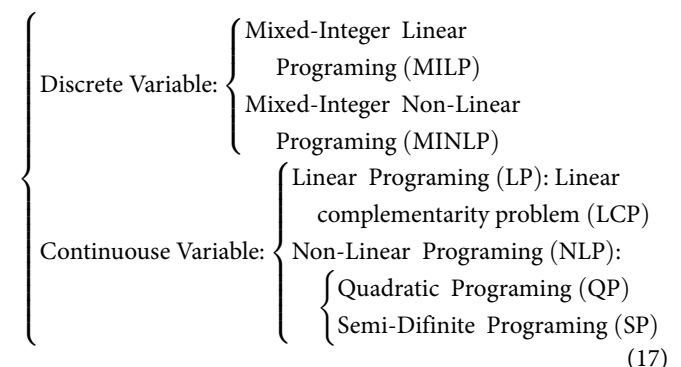
Based on the simplicity of the input data, the number of equations and size of the matrix of the equations (Calí and Borchiellini, 2002; Hassine and Eicker, 2011) as well as the accuracy of the results, the most frequent used method is a combination of Newton-Raphson and nodal head methods (Arsene et al., 2004; Hassine and Eicker, 2011). Due to weak convergence of the nodal equation algorithm for networks with low flow rate, another approach has been suggested by Arsene et al. (2004) called the

loop equation method, which is again a combination of a loop corrective and Newton-Raphson methods.

Further to the above mentioned studies, several commercial software have been developed based on the loop equation method using the graph theory, such as TERMIS⁵ or SpHeat (Eicker, 2004). Table 3 summarizes some of the current DHS modeling studies.

OPTIMIZATION OF DISTRICT HEATING SYSTEM

Different optimization methods have been developed in order to decrease the heat loss as well as the cost associated with operation and construction of the DHSs. Among various used methods, mathematical methods based on continuous or discrete variables, generic algorithm, neural network, and fuzzy logic systems are widely implemented techniques. Based on the defined type of the objective function, the DHS optimization is mainly formed on the basis of a single objective function or multi-objective functions. While most single variable function will be solved using the deterministic numerical methods, the multi-objective functions use either weighted factors or pareto-front approaches. In the weighted factor approach, importance factor is fitted to different objectives of the optimization problem, based on the trial-and-error approach, to convert the multi-objective function to single objective problem, which provides a numerical solution for the problem. The following chart shows different deterministic methods for the numerical optimization approaches.



where the optimization problem can be defined as (Caputo et al., 2013):

$$\min Z = f(x, y) \text{ s.t. } \begin{cases} h(x, y) = 0 \\ g(x, y) \leq 0 \\ x \in X, y \in \{0, 1\}^m \end{cases} \quad (18)$$

where the objective function $f(x, y)$ is subjected to the set of constraints. $h(x, y) = 0$ defines performance of the system, and $g(x, y) \leq 0$ stands for feasible plan of the system. Moreover, two different types of variables could be defined for MIP problems; the continuous variable (x), representing the state variable and the discrete variable (y) with the value of 0 and 1, representing the assignment of the equipment of a sequential task to the system.

⁵Termis District Energy Optimization Software. Available at: <http://software.schneider-electric.com/products/termis/>

TABLE 3 | Summary of the recent DHS modeling studies.

No.	Case study	Description	Country/ climate	Modeling level			Scale	Energy source	Utilized tools	Validation
				Source	Building	System				
1	Ancona et al. (2014)	34 Users	Italy		GD	P	M	CHP	ODS	TERMIS
2	Gopalakrishnan and Kosanovic (2014)	Combined sources		SM			M	Combined	UC	
3	Wang et al. (2013)	Multi-unit apartment building			GD	P	S	CHP	UC	
4	Weber et al. (2007)	8 U with different supply temperature	Geneva	SM	GD		M	CHP	UC	
5	Hassine and Eicker (2011)	7 users with $L_p > 13.5$ km	Germany		GD	P/T	L	Biomass	ODS	
6	Dalla Rosa et al. (2012)	Compares HT and LT supply	Ottawa		LF	P/T	L	CHP	Logster	TERMIS
7	Dalla Rosa and Christensen (2011)	Effect of human behavior	Denmark		LF	P	M	HP	IDA-ICE	TERMIS
8	Ben Hassine and Eicker (2013)	Thermal storage	Stuttgart		GD	P/T	L	CHP/ biomass		spHeat
9	Buoro et al. (2014)	Solar district heating		SM	GD		M	Solar/CHP	UC	
10	Hassine and Eicker (2014)	Solar thermal heating network	Sonnenberg	SM	Software	P/T	M	Geothermal/ solar		spHeat
11	Nuytten et al. (2013)	CHP with thermal storage for 100 U	Flanders	SM	Measurement	P	M	CHP	UC	
12	Noussan et al. (2014)	Biomass-fired CHP with storage	Leini/Turin	SM	Measurement		L	CHP/ biomass	UC	
13	Guadalfajara et al. (2014)	For 50% heating load calculation	Zaragoza	SM	TRNSYS		L	Solar	UC	
14	Hlebnikov and Siirde (2009)	Source optimization	Estonia	SM			L	CHP	UC	
15	Kuosa et al. (2013)	Different flow control strategy			GD	P/T	M	CHP/HP	UC	
16	Pirouti et al. (2013)	Different control strategy	Wales		HDD	TPL	M	CGP	PSS SINCAL	
17	Sanaei and Nakata (2012)	City level	Yazd	SM	GD		L	Combine	EMD	
18	Verda et al. (2012)	Neighborhood	Turin		HDD					

SM, source modeling; GD, given data; LF, load factor; HDD, heating degree day; P, pressure model; T, thermal model; ODS, own developed software; UC, user code; L, large; M, medium.

Optimization algorithms consist of both continuous and discrete variables where they furthermore characterized as mixed-integer linear programming (MILP) if all the equations are linear or mixed-integer non-linear programming (MINLP) if one of the equations is non-linear. In the cases of having no discrete variable, the optimization algorithm can be addressed with linear programming and non-linear programming (Biegler and Grossmann, 2004).

The schematic of the optimization process, presented in Eq. 17, serves as a basis of several optimization tools, which have been developed for optimization of the DHSs, e.g., general optimization toolboxes such as MATLAB or GenOpt (Attia et al., 2013), customized DHS optimization tools such as FreeOpt

(Akhtari et al., 2014), cost-associated optimization tools with the thermal electrical load of the system such as STEFaN (Connolly et al., 2014), network pipe size and routing optimization tool such as MODEST (Model for Optimization of Dynamic Energy System with Time-Dependent and Boundary Condition), the system investment, and operational cost optimization at both supply and demand level (Henning, 1999).

Regardless of the type of optimizing algorithm, the main objective of such models is to minimize the operational cost, investment cost, and heat demand of the system in addition to minimizing the environmental impacts such as CO₂ emission (Lu et al., 2014). **Table 4** summarizes some of the recent DHSs optimization studies.

TABLE 4 | Summary of the recent DHS optimization studies.

No.	Reference	Type of objective function	Objectives	Solving method
1	Falke et al. (2016)	Multi-objectives optimization	Cost and CO ₂ emission	Evolutionary algorithm/Perato front
2	Li et al. (2016b)	Multi-objectives optimization	Cost and CO ₂ emission	Weighted factor/MILP
3	Li et al. (2016a)	Single objective	Pressure drop	Deterministic/MINLP
4	Mertz et al. (2016)	Multi-objectives optimization	Global cost, operation, and investment	Weighted factor/MINLP
5	Wang et al. (2016)	Multi-objectives optimization	Accumulated error	GA/non-linear objectives
6	Lu et al. (2014)	Multi-objectives optimization	Exergy efficiency and life cycle global warming	GA/multi-objectives
7	Gopalakrishnan and Kosanovic (2014)	Single objective	Hourly cost	GA/MINLP
8	Buoro et al. (2013)	Multi-objectives optimization	Global cost and CO ₂ emission	Weighted factor/MILP
9	Wang et al. (2013)	Single objective	Mass flow rate/thermal conductance	Newtown method
10	Keçebas et al. (2013)	Multi-objectives optimization	Total cost	ANN
11	Keçebaş and Yabanova (2012)	Single objective	Mass flow rate	ANN
12	Verda et al. (2012)	Multi-objectives optimization	Average unit cost of heat supplied to all users	GA
13	Sanaei and Nakata (2012)	Single objective	Exergy efficiency	Non-linear GRC
14	Åberg and Henning (2011)	Single objective	Operational cost	MODEST optimization model
15	Dobersek and Goricanec (2009)	Single objective	Capitalized cost	NLP
16	Söderman (2007)	Multi-objectives optimization	Total cost	Weighted factor/MILP
17	Henning et al. (2006)	Single objective	Operational cost	MODEST optimization model
18	Wright et al. (2002)	Multi-objectives optimization	Operational cost and thermal comfort	GA/multi-objectives

MILP, mixed-integer linear programming; MINLP, mixed-integer non-linear programming; GRG, generalized reduced gradient.

CONCLUSION

In this paper, the state of the art of modeling and optimization of DHSs is reviewed and limitations of the previous works have been summarized. One of the major limitations of the existing works is addressed as the procedure that could be used in predicting the demand load of the entire district network. In general, there are different methods suggested to model and predict the demand profile in DHSs. Many of these methods predict the energy demand of a building in terms of its maximum value, while others predict the actual profile of the system in a smaller interval such as an hourly basis. This limitation becomes more important in case of larger DHSs in which building heterogeneity is elevated. **Table 1** summarizes the different approaches that have been used in predicting the load of the DHSs. It was concluded that most of the utilized approaches are only applicable to one type of building.

Also, the accuracy of the predictions of previous works has been addressed in **Table 2**. Since most of the existing models do not take into consideration the effect of the occupants' behavior in their modeling, the accuracy of the prediction, particularly at the building level, is much lower in the previous works. In contrast, the accuracy significantly increases when the entire DHS is considered. This phenomenon can be observed in previous works focused on DHSs with similar building types. Since more than one building is involved in the profile prediction of an entire

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district network, their demand profiles overlap and therefore compensate the accumulated error in the load prediction; this process significantly increases prediction accuracy.

In terms of the distribution network, the existing works has been categorized in three levels, small size, mid-size, and large systems. This categorization has been summarized in **Table 3**. Even though in the mid-size and large size networks, there is a higher heat loss ratios, thermal insulation of the distribution network is suggested to be a major drawback; however, for the newer DHS generations, working with lower temperature, this loss can be embedded as an into the demand load. Regarding the state of the art of the optimization methods, **Table 4** provides a summary on the basis of their objective functions.

AUTHOR CONTRIBUTIONS

BT, first author. PM, second supervisor. AB, collaborator. FH, first supervisor.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Concordia University for supporting this research through the Concordia Research Chair program.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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