



HAL
open science

Production planning for district heating networks: A sequential method to consider share of renewables in annual heat production

Xinyu He, Cong Toan Tran, Assaad Zoughaib

► **To cite this version:**

Xinyu He, Cong Toan Tran, Assaad Zoughaib. Production planning for district heating networks: A sequential method to consider share of renewables in annual heat production. Energy Reports, 2021, 7, pp.237-243. 10.1016/j.egy.2021.08.151 . hal-03507880

HAL Id: hal-03507880

<https://hal.science/hal-03507880>

Submitted on 5 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

International Symposium on District Heating and Cooling, 17th, Sep. 2021, Nottingham, UK

Production planning for district heating networks: a sequential method to consider share of renewables in annual heat production

Xinyu HE^a, Cong Toan TRAN^{b*}, Assaad ZOUGHAIB^b

^a*SPEIT, Shanghai Jiao Tong University, 800 Road Dongchuan, Minhang District, 200240 Shanghai, China*

^b*MINES ParisTech, PSL Research University, CES : Centre for Energy Efficiency of Systems, 5, rue Léon Blum, 91120 Palaiseau, France*

Abstract

A district heating network has generally more than one production unit, and then there are different ways to fulfill the energy demand of the network. This paper deals with the planning problem which is a problem of optimization under constraints. The production units are modeled using MINLP (mixed integer non-linear programming), in particular the following technical aspects are considered: storage capacity (for municipal wastes and biomass), allowable operating range, allowable variation of power over time, partial load performances, minimum working time when a unit runs, and minimum waiting time when it is in stand-by mode. The environmental constraint is the annual share of renewable energies in the global energy mix (for example, at least 50 % over a year). The model aims to minimize the operating cost of the network. The problem cannot be solved by a one-shot optimization, so the paper proposes a sequential approach: first, a target of renewable share is calculated for each month of the year; secondly, the planning production is determined each day according to the calculated target. The results of a case study show that the planning strategy that only aims to minimize the operating cost violates the environmental constraint. Using the developed planning model raises a little bit the cost (4.5%) but fulfills the heat demand and environmental constraint at the same time. Considering a reduced VAT eligible in France when the constraint on renewable share is met, the proposed planning is even better in term of the total cost (10 % lower).

Keywords: district heating network; planning problem; optimization; MINLP

1. Introduction

District heating networks (DHN) play an important role in heating delivery in urban areas; it may provide heat at a lower cost and with lower environmental impacts compared to using individual heating systems (Pirouti et al., 2013)(Li et al., 2016). One of the common problems in monitoring is the planning problem. A network has generally more than one production system, and then there are different ways to fulfill the energy demand of the network.

The planning problem of DHN is not a new problem. (Sameti and Haghghat, 2017) have discussed different types of optimization, constraints and techniques as well as the optimization tools used in DHN. (Stange et al., 2018) have combined the existing methods for operational optimization and the demand forecasting algorithm. (Talebi et al., 2016) have made a review of the different modeling approaches and the optimization methods to reduce the operating cost. (Schweiger et al., 2017) have provided a method based on dynamic optimization and the language Modelica.

Almost the available methods focus only on optimizing the cost, but do not take into account CO₂ emission when setting up the operational planning. And yet, CO₂ emission is playing a more and more important role nowadays, because it has impacts not only on the environmental aspect, but also on the economic one. For example, in France, there is a reduced VAT (value added taxes) for a district heating station once its renewable share in the global heat production is high enough (over 50% for a whole year). Considering CO₂ emission when setting up the operational

planning is not a trivial, because the horizon of the corresponding optimization problem is quite long (e.g. 1 year). In this context, the paper proposes a planning method which aims to optimize the operating cost while considering the constraint of renewable share. The method takes into account the main characters of the production units, such as storage capacity, allowable operating range, allowable variation of power over time, partial load performances, minimum working time when a production unit runs, and minimum waiting time when it is in stand-by mode.

2. Methodology

The method includes two models: prediction model and optimization model. The prediction model will predict the heat demand of the clients during a day depending on the weather forecast (temperature) and some other characters of the day (whether it is weekend or holiday). The optimization model aims to determine the planning (i.e. the production units to be used and their heating powers) which fulfills the heat demand while optimizing the cost and satisfying different operating constraints and renewable share criteria. In what follows these models will be described.

2.1. Heat demand prediction model

Regression model has been chosen considering its reasonable computing time and its appropriateness for daily use. More specifically, the ARMAX (AutoRegressive-Moving-Average model with eXogenous inputs) model is used, because it is well-known that the model gives an acceptable precision (Fang and Lahdelma, 2016). Basically, an ARMAX model is made up of three parts: one auto-regressive part, one part depending on the exterior data, and the third part is the error:

$$y_t = \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \eta_j x_{t-j+1} + e_t \quad (1)$$

where: t: time t
y: heat demand
x: vector of independent variables (e.g.: outdoor temperature, time...)
e: error of the model
 φ, η : parameters of the model
p, q: orders of the model

The heat demand at time t depends not only on the independent variables, but also on its values at t-1, t-2 ... For each pair of model orders (p, q), the parameters (φ, η) are determined using the least squares method with the historical data of the network, in other words the parameters are looked for to minimize the sum of the squares of the error e.

The performance of the model depends on the independent variables taken into consideration and on the orders (p, q). Four types of model are built up:

- Model «T»: only the outdoor temperature is considered as independent variable
- Model «T72»: in addition of the outdoor temperature, 72 variables are used to represent the hours of a day: 24 variables for Sunday, 24 variables for Saturday and 24 variables for weekday (from Monday to Friday)
- Model «T72w»: similar to the model «T72» but Wednesday is considered as Sunday (in fact, schools are closed on Wednesday in some regions in France, so that the housing energy consumption on Wednesday is closed to the one on Sunday).
- Model «T72h»: similar to the model «T72» with an additional variable to indicate if a day is in a holiday period.

For each of these types, 21 combinations of the order (p,q) are considered, where p's value is between 0 and 6 and q's value is between 0 and p-1.

In order to quantify the accuracy of the models, the average mean absolute percentage error is used:

$$AMAPE = \frac{1}{N} \sum_{t=1}^N \frac{|\hat{y}_t - y_t|}{\frac{1}{N} \sum_{t=1}^N y_t} \quad (2)$$

where: y : real heat demand
 \hat{y} : heat demand calculated by the prediction model
 t : time t
 N : the number of time steps during the evaluation period

2.2. Optimization model

Because the renewable share must be calculated over a long period (1 year), it is not possible to solve the problem by a one-shoot optimization. For this reason, the method uses a sequential approach, so that the optimization model includes two sub-models, daily model and monthly model. While the monthly model determines a target of renewable share for each month of the year, the daily model aims to give the best planning solution during a day by following the determined targets. Both models use the MINLP (mixed integer nonlinear programming) and the multi-period approach. More specifically, continuous variables are used to represent the heating powers, binary variables to represent the status of the production units (on/off) and nonlinear equations to consider different constraints. For a given optimization horizon (e.g. 1 day), the problem is split into a number of periods with a step of time of 1 hour. The objective functions of both models are the operating cost calculated for the whole optimization horizon.

2.2.1. Monthly model

This model aims to determine the renewable share for each month of the year. The following constraints are considered:

- Lower limit and upper limit of the operating range of the production units
- Partial load performances
- Annual renewable share should be higher or equal than a threshold value (e.g. 50%)

To limit the calculation time, each month of the year is represented by one typical day of which the heat demand is known (using historical data of the network).

2.2.2. Daily model

The daily model aims to determine the daily planning. The following constraints are considered for all the production units:

- Lower limit and upper limit of the operating range of the production units
- Upper limit of the variation of power over time
- Minimum waiting time in the stand-by mode when a production unit is turned off;
- Minimum working time when a unit is turned on;
- Combustible storage capacity (for biomass and waste incinerators)
- Daily renewable share should be equal to the target fixed by the monthly model

The whole process of the method is shown in Fig. 1. On the first day of each month, the monthly model is run to identify a target of renewable share for that month. Note that the monthly model takes into account the actual energy production mix of the months prior to that day. Each day, the prediction model is run to calculate the heat demand, and then the daily model is used to determine the production planning.

The proposed method aims to optimize the rate of heat production, and does not consider the supply temperature of DHN. In other words, the method is appropriate to be used when the network operating cost depends only on the heating powers provided by the production units, and not on the supply temperature (that is true for a number of production systems such as gas boiler, waste or biomass incinerators).

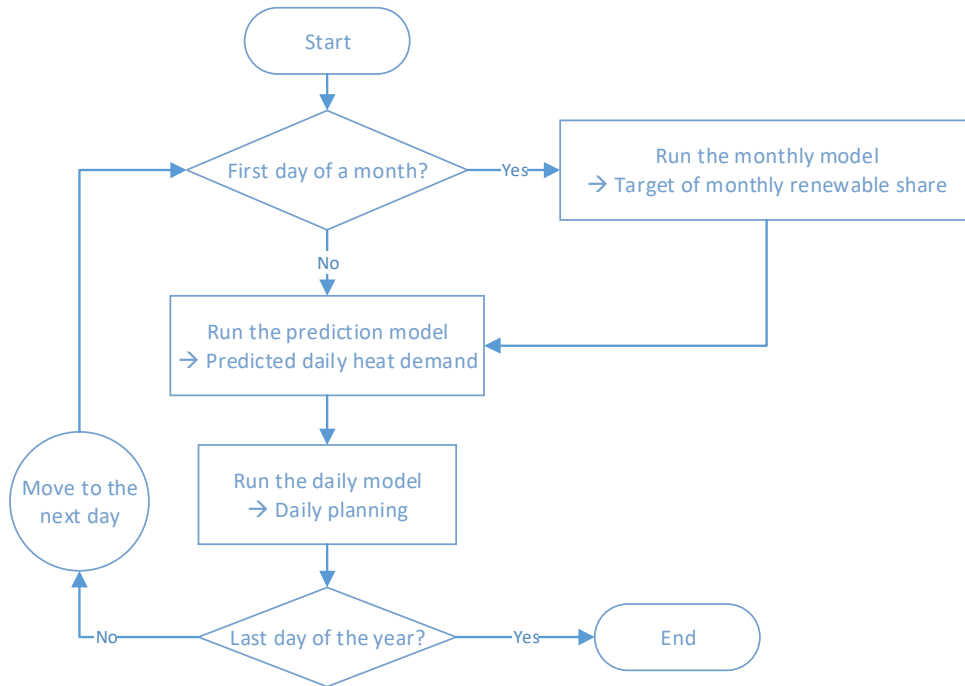


Fig. 1. Proposed planning method

3. Case study

The presented method is implemented in Python, using Pyomo package (Hart et al., 2017) for the optimization part. It is tested on a case study inspired from a real DHN in Paris.

3.1. Description of the case study

The DHN has four production units: two gas boilers, one Circulating Fluidized Bed (CFB) using biomass and one municipal waste incinerator. The gas boilers are considered as non-renewable source, while the CFB and incinerator as renewable energies. Each machine has different characteristics, which are given by the network operator and listed in Table 1.

Table 1. Characteristics of the production units

	Gas1	Gas2	CFB	Incinerator
Minimum heating power (MW)	0.01	0.01	2	2
Maximum heating power (MW)	20	20	25	15
Maximum variation of power over time when power increases (MW/hour)	20	20	7	3
Maximum variation of power over time when power decreases (MW/hour)	20	20	10	5
Cost (€/MWh)	90	91	150	1
Minimum waiting (working) time (hour)	0	0	6	24

In the real life, the 2 gas boilers Gas1 and Gas2 are exactly the same, but a little difference for the cost for producing the heat is set, only to force to use only one gas boiler if its power is enough to satisfy the demand. That technique also allows to reduce the calculation time required by the solver. Indeed, if the 2 boilers have exactly the same cost, there are a number of equivalent planning solutions which have the same network operating cost and the solver may take time to differentiate them. For the incinerator machine, since it uses garbage as the source for producing heat, there is actually no cost for buying the combustible. As the capacity of the storage room is limited, garbage has to be sometimes burned even if it is not necessary to produce heat, because there is no place to stock the coming garbage. In that case, the total heat produced by the network will be higher than the demand required by the end-users, the difference is released to the atmosphere via a cooling tower. In order to avoid wasting the heat produced by the incinerator, a small cost is set for the machine. In this case study, the minimum renewable share of a whole year is set to 50%.

To quantify the performance of the proposed method of planning, 3 test scenarios are set up:

- Scenario 1: the full presented method is applied to plan the network
- Scenario 2: the unique constraint on the renewable share (50%) is set for every day of the year. In this scenario, the monthly model is not used, only the daily one is.
- Scenario 3: the constraint on the renewable share is not considered at all, and the model only aims to optimize the cost

3.2. Results

3.2.1. Performances of the prediction models

84 prediction models are tested (21 combinations of order for each of four types of model). It is found that for summer, the model « T72v » with the order (4,2) is the best one and for winter, the model « T72v » with the order (2,1) is the best. The value of AMAPE during the year is 0.048, in other words, there is a 4.8% difference between the real demand and the predicted demand. With the average annual heat demand equals to 30.6 MW, the annual average difference between the real and predicted demands is 1.46 MW. As example, Fig. 2 shows the performance of the selected prediction model during a day. The predicted demand follows the same trend with the real demand, even though there is sometime significant difference between these 2 quantities.

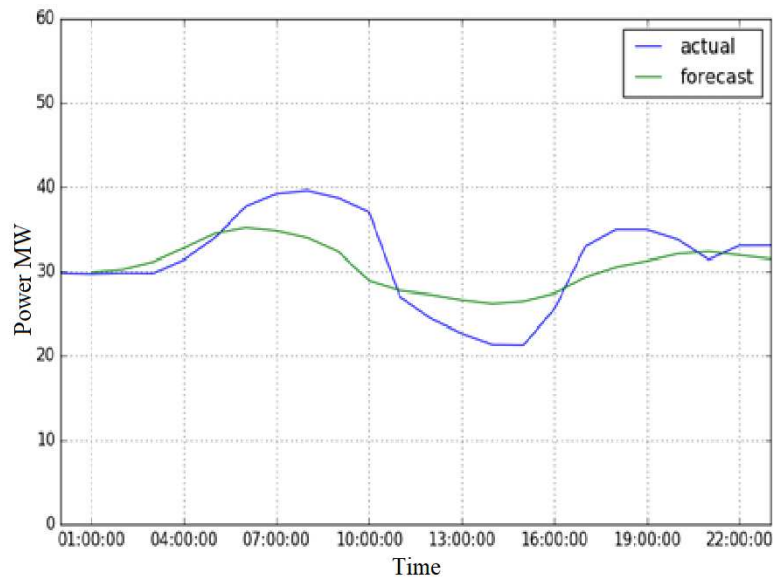


Fig. 2. Comparison between the predicted heat demand and the actual one

3.2.2. Performances of the optimization model

When simulating the HEN during a whole year, the planning determined by the optimization model is adjusted continuously in order to meet exactly the heat demand of the end-users. That is because there is always a difference between the real demand and the predicted one. When the real demand is higher than the predicted one, the planned heating powers are increased by preferring the cheapest production units first. On another side, when the real demand is lower than the predicted one, the planned heating powers are decreased by preferring the most expensive production units first. In both cases, the change of power is only allowable if it satisfies the technical constraints (i.e. operating range, limited variation of power over time, minimum working or waiting time). The planning is considered as failed when it is not possible to satisfy the technical constraints and fulfil the real demand at the same time.

Table 2 presents the results of the three tested scenarios. By definition, the failure rate is the time, in percentage, when the network fails to satisfy 100 % of the real heat demand. The results show that the demand is fulfilled in all the time in the scenario 2, the failure rates of the scenarios 1 and 3 are negligible (0.19 % and 0.27 %, respectively). Then, it can be concluded that all three scenarios ensure the thermal comfort of the clients.

In the scenario 3 where the model optimizes only the cost without considering the constraint of renewable share, the planning is unacceptable because the annual renewable share does not meet the criteria of 50 %. The scenario 2, that sets the target of renewable share to 50 % everyday, shows the highest cost. Note that the annual renewable share overpasses the target. Indeed, the renewable share of the periods of low demand exceeds what is required, because only the incinerator is enough to fulfil the heat demand. In the scenario 1 that corresponds to the proposed method of planning, the daily target varies month by month, and that allows the DHN to have an annual renewable share very close to the desired value (50 %). The corresponding cost is lower than the one of the scenario 2 (about 6.2 %), but higher than the scenario 3 (about 4.5 %). However, the expected gain thanks to the reduced TVA¹ is 14.5 %, and that makes the scenario 1 the most attractive scenario in term of the cost (about 10 % less than the scenario 3).

Table 2. Results of the planning model

Scenario	Annual cost (M€)	Annual renewable share	Failure rate
1	16.10	50.1%	0.19 %
2	17.16	56.6%	0
3	15.40	45.9%	0.27 %

As example, Fig. 3 shows the heating powers of the four production units during 10 days (results from the scenario 1). The waste incinerator usually runs at its maximal power, because it is not only a renewable source but also the cheapest production unit. From time to time, its power is reduced when the demand is low, and that allows to store garbage for further use. The gas boiler 1 is used almost all the time because gas is the second cheapest combustible. The second gas boiler 2 is used only when the first one reaches its maximum power. The CFB is less used since it is the most expensive unit; it is used in order to satisfy the constraint on the renewable share.

¹ In France, the normal TVA is 20 %, while the reduced one is 5.5 %

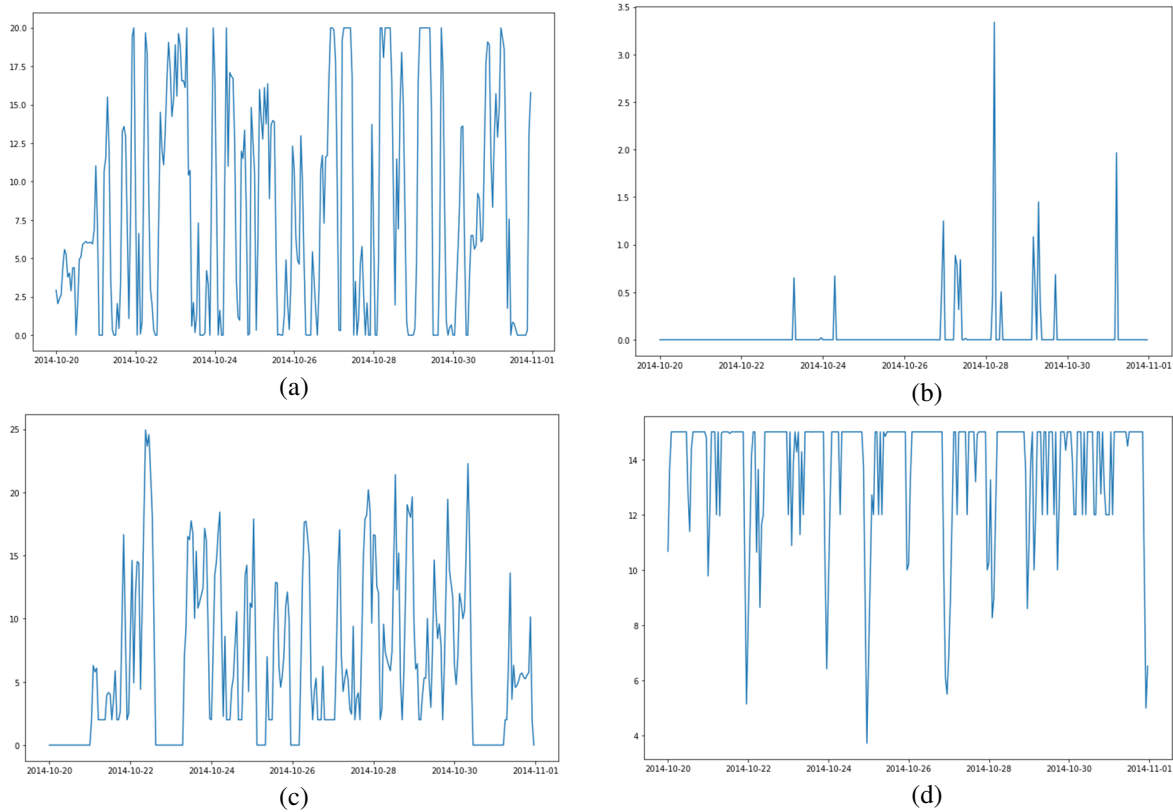


Fig. 3. Heating power (in MW): (a) gas boiler 1; (b) gas boiler 2; (c) CFB; (d) incinerator

4. Conclusion

This paper has built a model for planning the operation of a DHN composed of various production units. The model aims to minimize the operating cost, but the annual renewable share in the energy production mix has to satisfy a local regulation (at least 50 % in the case study). The model considers a number of technical constraints on the production units such as allowable operating range, allowable variation of heating power over time and minimum working (waiting) time. The proposed method of planning uses a sequential approach and is composed of two MINLP sub-models. The monthly model aims to determine the daily target of renewable share and the daily model identify the daily planning.

The case study is inspired from a DHN in Paris. The results show that the proposed method of planning allows to keep the annual renewable share to the desired value (50 %). The operating cost is higher than the case where only the cost is optimized without considering the constraint of renewable share. However, taking into account the reduced TVA, the planning provided by the method is in fact the most attractive one in term of the total cost (10 % lower). This result indicates a tax subsidy may really encourage the operators of DHN to use more and more renewable energies.

The corresponding cost is also 6.2 % lower than the case where a unique target of renewable share is set for everyday. Then, it can be concluded that using the monthly model to determine the target month by month helps optimizing the cost while maintaining the annual renewable share under control.

In the further work, the supply temperature of the network will be considered, allowing the method to be applied in the cases where the performance of the production units highly depends on the temperature, such as geothermal or heat pump.

References

- Fang, T., Lahdelma, R., 2016. Evaluation of a multiple linear regression model and SARIMA model in forecasting heat demand for district heating system. *Appl. Energy* 179, 544–552. <https://doi.org/10.1016/j.apenergy.2016.06.133>
- Hart, W.E., Laird, C.D., Watson, J.-P., Woodruff, D.L., Hackebeil, G.A., Nicholson, B.L., Siirola, J.D., 2017. *Pyomo--optimization modeling in python*, Second. ed. Springer Science & Business Media.
- Li, L., Mu, H., Li, N., Li, M., 2016. Economic and environmental optimization for distributed energy resource systems coupled with district energy networks. *Energy* 109, 947–960. <https://doi.org/https://doi.org/10.1016/j.energy.2016.05.026>
- Pirouti, M., Bagdanavicius, A., Ekanayake, J., Wu, J., Jenkins, N., 2013. Energy consumption and economic analyses of a district heating network. *Energy* 57, 149–159. <https://doi.org/https://doi.org/10.1016/j.energy.2013.01.065>
- Sameti, M., Haghghat, F., 2017. Optimization approaches in district heating and cooling thermal network. *Energy Build.* 140, 121–130. <https://doi.org/10.1016/J.ENBUILD.2017.01.062>
- Schweiger, G., Runvik, H., Magnusson, F., Larsson, P.-O., Velut, S., 2017. Framework for dynamic optimization of district heating systems using Optimica Compiler Toolkit, in: Kofránek, J., Casella, F. (Eds.), *Proceedings of the 12th International Modelica Conference*, Prague, Czech Republic, May 15-17, 2017, Linköping Electronic Conference Proceedings. Linköping University Electronic Press, p. 132:013. <https://doi.org/10.3384/ecp17132131>
- Stange, P., Matthees, A., Sander, T., 2018. Operational optimization of energy systems, 25 years – established and promising use cases. *Energy Procedia* 149, 15–24. <https://doi.org/https://doi.org/10.1016/j.egypro.2018.08.165>
- Talebi, B., Mirzaei, P.A., Bastani, A., Haghghat, F., 2016. A Review of District Heating Systems: Modeling and Optimization. *Front. Built Environ.* 2, 22. <https://doi.org/10.3389/fbuil.2016.00022>