

A DYNAMIC PRICING MECHANISM FOR DISTRICT HEATING

REPORT 2017:408



FJÄRRSYN



Energiforsk

A Dynamic Pricing Mechanism for District Heating

Based on levelized cost of heat and prediction of total heat demand

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ISBN 978-91-7673-408-7 | © ENERGIFORSK June 2017

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Foreword

Inspired by the findings and conclusions that came forth in an earlier project – the business logic and business models of district heating – in the research programme Fjärrsyn, many district heating companies reviewed and developed their price models to better reflect the capacity called for by district heating customers and consequently to better mirror the cost structure of the district heating companies. In this process the idea of pricing the demand for heat power as accurately as possible has gained foothold among district heating suppliers. The study presented in this report takes the idea to its extreme and explores the possibility of developing a mechanism for a wholly dynamic pricing of the demand for heat power.

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The project been followed by a project reference group including Jan Andhagen from Mälarenergi, Emil Berggren from Tekniska Verken i Linköping, Patrik Holmström from Energiföretagen Sverige and Tommy Jönsson from Sala-Heby Energi.

The project is part of the research program Fjärrsyn, which is financed by Energiföretagen Sverige and the Swedish Energy Agency. The research in Fjärrsyn intends to strengthen district heating and cooling, encourage the development of competitive businesses and technologies and create resource-efficient solutions for the sustainable energy system of the future, for the benefit of the energy industry, the customers, the environment and the society at large.

Anders Ericsson
Chairman of the Market Council at Energiföretagen Sverige

Reported here are the results and conclusions from a project in a research program run by Energiforsk. The author / authors are responsible for the content and publication which does not mean that Energiforsk has taken a position.

Sammanfattning

Fjärrvärmebranschen står inför flera utmaningar under de kommande åren. En kombination av högre driftskostnader, konkurrens från alternativ uppvärmningsteknik som gynnas av låga elpriser, samt ett behov av att ge mer transparent och tydlig prisinformation till slutanvändarna ställer höga krav på många fjärrvärmeföretag. Det generella syftet med detta projekt har varit att utveckla och utvärdera en dynamisk prismekanism som fortsatt kan främja konkurrenskraftiga leveranser av fjärrvärme.

En bra prismodell ska kunna spegla den aktuella produktionskostnaden så noggrant som möjligt, och därför motivera slutanvändarna att både minska effektopparna och energiförbrukning. Samtidigt ska fjärrvärmepriset vara både förutsägbart och transparent. En ny dynamisk prismodell som baseras på momentana produktionskostnaden av en kilowattimme (eng. levelized cost of energy, LCOE) har utvecklats. Beräkningarna beaktar olika bidragande faktorer som kapitalkostnader, drift- och underhållskostnader samt andra övriga kostnader.

Jämfört med de nuvarande prismodellerna så visar den föreslagna prismekanismen en potential för att sänka värmepriset. Det dynamiska värmepriset varierar med produktionskostnaden, som i sin tur beror av värmebehovet i den aktuella drifttimmen. Ett dynamiskt värmepris skulle därför kunna öka kunders motivation att minska värmeförbrukning under systemets effektoppar. Komplexiteten uppstår exempelvis bränslekostnader ska fördelas mellan samtidig produktion av el respektive fjärrvärme, vilket kan hindra dess praktiska tillämpning och samtidigt göra prissättningen svårare att förstå. Varierande och temporär användning av vissa anläggningar i kombination med oförutsedda underhållskostnader kan även leda till stora avvikelser då det momentana värmepriset (LCOH) beräknas.

Dynamiska prognoser av värmebehovet ligger till grund för prismodellen. Lastprognosen baseras på ett neuralt nätverk (ENN) som har tränats med ingångsparametrar som utomhustemperatur, vindhastighet och direkt solinstrålning. Det genomsnittliga absoluta procentuella felet uppgår till cirka 6 %.

Att reformera prismodellerna kan väsentligt bidra till att förändra kunders fjärrvärmekostnader, och samtidigt påverka valet av energibesparande åtgärder. Tre alternativa uppvärmningslösningar har utvärderats i denna studie: Fjärrvärme för basbehov i kombination med direktverkande elvärme för topeffekter; Värmepump för basbehov i kombination med fjärrvärme eller direktverkande elvärme för topeffekter. De nuvarande låga elpriserna resulterar i att fjärrvärme som kompletteras med direkt elvärme för spetsbehov eller att använda värmepump för basbehov i kombination med fjärrvärme för spetsbehovet utgör de bästa ekonomiska alternativen jämfört med enbart fjärrvärme. Lönsamheten för dessa två teknikalternativ blir lägre med en ny dynamisk prismodell jämfört med de befintliga prismodellerna. Detta indikerar att en dynamisk prismodell är mer konkurrenskraftig än de traditionella modellerna.

Summary

District heating (DH) companies are facing several challenges during the upcoming years. A combination of higher operational costs, competition from alternative technologies benefiting from low electricity prices, as well as the need of providing more transparent price information to the end-users puts high pressure on many utilities. The general purpose of this project is to develop a new dynamic pricing mechanism, which can promote the competitiveness of DH.

A good price model should be able to reflect the dynamic production cost accurately and motivate consumers to reduce the peak load and save energy at the same time. In addition, the heat price should be predictable and transparent. A novel dynamic price model has been developed based on the levelized cost of energy, which carefully considers the capital cost, O&M cost and other costs. Comparing to the current real price models, it can reflect the production cost in a better way and is more transparent. Meanwhile, the price based on levelized cost of heat (LCOH) varies with the production, which is further determined by the total heat demand; hence, it can influence the behaviors of customers, especially during the peak price time. It is easy to understand; whereas, its complexity, for example the allocation of fuel cost for the production of electricity and heat in a CHP system, may hinder its practicable application. Moreover, the dynamic operation hours of equipment and unpredictable maintenance cost could also introduce large deviations in the calculation of LCOH. Dynamic prediction of the total heat demand in the network is the basis for the dynamic pricing model. A model based on Elman neural network (ENN) has been developed with the ambient temperature, wind speed and direct solar radiance, as key input parameters. Its overall mean absolute percentage error is around 6%.

Price model reforming could lead to a significant change in the expense of customers and affect the selection of energy saving measures. Three alternative solutions to DH are assessed in this study: using direct electrical heating (DEH) to provide the peak heating demand combined with DH covering base demand; installing a ground source heat pump (HP) to cover base demand combining with DH or DEH to provide peak demand. Results show that due to the low electricity price currently, using DEH to cover the peak demand of district heating and combining DEH and HP can be more economical than DH. Compared with the real price models, the annual cost saving becomes smaller when the proposed dynamic price model is applied, which implies a better competitiveness.

List of content

1	Introduction	8
2	Current situation about heat pricing	9
2.1	DH pricing in a regulated market and a deregulated market	9
2.1.1	Cost-plus pricing	9
2.1.2	Marginal cost pricing	10
2.2	Marginal cost model	10
2.3	Price component in sweden	11
2.4	Pricing dilemma	12
2.5	Need of dynamic pricing mechanisms	13
3	Dynamic pricing mechanism	14
3.1	Levelized cost of heat	14
3.2	LCOH for CHP	14
3.3	Case study	15
3.4	Model comparison	21
4	Prediction of the total heat demand	22
4.1	Model description	22
4.2	Key input factors	24
4.3	Discussion	29
5	Influences of new price model	30
5.1	Influences on consumers	30
5.2	Influences on selecting energy saving measures	31
6	Concluding remarks	34
7	References	36

Acknowledgement

First of all, the financial support from Energimyndigheten and Energiforsk under the program of Fjärrsyn is gratefully appreciated.

We would also like to thank all members of the reference group: Tommy Jönsson, from Sala Heby Energi, Emil Berggren, from Tekniskaverken i Linköping, Jan Andhagen, from Mälarenergi, and Patrik Holmström, from Energiföretagen Sverige, for their valuable comments and guides during the project.

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2017/04/30

1 Introduction

A District Heating (DH) system is a centralized system that distributes steam/hot water through a pipeline network to satisfy end-users' heat demands. The centralized heat generation benefits from the higher efficiency and more advanced control on pollutant emission. District heating is the most common way to distribute heat in Sweden [1]. There are more than 200 DH companies with over 400 DH systems in Sweden. For multi-dwelling buildings and non-residential premises DH accounts for 92% and 80% of the market share respectively. Sweden has an ambition to reduce 20 % of the energy demand in the building sector by 2020 [1]. To achieve this goal, DH would play a significant role.

However, due to the continuous rise in cost of DH, it faces big challenges to further improve efficiency, reduce cost and enhance profitability. The competitiveness of DH systems for a particular building/house owner depends on three factors: (I) the price of the DH, (II) the price of the fuel or electricity used to heat the building and the expected increase in those prices, and (III) the efficiency with which that fuel is used compared to the efficiency of the potential DH [2]. According to the Energy Markets Inspectorate (EMI) [3], DH, geothermal heat pumps and wood pellets are on the same competitive level for the typical multi-dwelling buildings in Sweden.

Real-time pricing (RTP) in the electricity sector has proved remarkably efficient in demand-side management, increasing the profit of electricity suppliers and improving the transparency in pricing mechanisms. Therefore, developing a new heat pricing mechanism can be a key to achieve the sustainable development of the heating market.

The general purpose of this project is to develop a new dynamic pricing mechanism, which can promote the competence of DH. The specific objectives include:

- Understanding the needs of both DH companies and customers more deeply and identifying the problems about the current price models
- Developing new models that can predict the total heat demand in the network more accurately. The forecasted total heat demand will provide the basis for the determination of the dynamic price.
- Evaluating the impacts of the new price model on the income of DH companies and energy expense of consumers.

2 Current situation about heat pricing

The pricing mechanism defines the way, in which DH companies charge their customers for their service. Due to the monopoly nature, the DH company dominates in pricing of heat and the price elasticity is low in the heat market. The overall cost of DH generally depends on three main factors: (1) the connection costs for customers, (2) the costs of a distribution network, which depend on the size of the DH network and its thermal loads, and (3) the production costs of thermal energy.

2.1 DH PRICING IN A REGULATED MARKET AND A DEREGULATED MARKET

Worldwide, there are two main types of DH market, namely the regulated and deregulated. There are two representative methods used to price DH: the cost-plus pricing method, which is often used in regulated DH markets, and the marginal-cost pricing method, which is commonly used in deregulated heating markets [4].

2.1.1 Cost-plus pricing

Cost-plus pricing offers a number of advantages to sellers, buyers and regulators, such as simplicity, flexibility and ease of administration. However, a regulated market does not allow DH companies to compete with other heating solutions by adjusting DH prices, while the subsidization of DH systems is often needed in order to make DH as a competitive option as its alternatives, e.g. oil boilers, gas boilers and electricity-driven heat pumps. The subsidy on DH systems is important in terms of stabilizing local energy prices, developing local energy systems, saving imports of energy, reducing ambient pollution, and creating jobs. The size of the subsidy can be calculated by referring to the value of these goals [5]. However, cross-subsidies may impact adversely on both the DH sector and other sectors [6]. In addition, the cost-plus method is usually based on the historical data of real plants, which contains uncertainties when applied to the projection of future situations.

Under a cost-plus pricing mechanism, DH companies have incentives to increase profits by inflating costs, since permitted profits are usually related to costs [7]. The DH companies would be punished and allowed for a lower level of permitted profits, if they are operating on a lower cost than the reported level [6, 8]. Consequently, the cost-plus pricing method undermines suppliers' incentives to reduce costs and to upgrade their technologies. In addition to this, changes in real fuel costs cannot be transferred to consumers due to the use of historic data, and this prevents DH producers from generating enough profit to budget for necessary maintenance and improvements. In the long run, DH tariffs based on the cost-plus pricing approach will affect the efficiency of the DH market.

2.1.2 Marginal cost pricing

A marginal cost is the cost of one more unit of product, which in this case is the cost of generating one more unit of heat through DH [9, 10]. According to Economic theory, the market price is obtained at the equilibrium point where the total amount of heat supply is equal to the entire heat demand. Facing the exogenous market price, a DH supplier can take a larger market share and gain more profits by setting its price at a lower level than the market price. As the DH price is based on the supplier's marginal cost, every supplier is motivated to reduce costs, promote efficiency, and invest in infrastructure and equipment. Consequently, pricing DH according to marginal costs will benefit not only DH producers, but also the environment in terms of reduction in CO₂ emissions and other pollutants. In practice, a marginal cost is usually calculated by splitting a total cost into a fixed and a variable cost. The marginal cost is thus equal to the additional unit of variable costs plus the depreciation of fixed costs. In this way, the marginal cost approach provides a clear route to understanding and managing the behavior of costs.

However, when a DH company has been determining DH price according to its marginal costs, which in turn largely depend on variable costs, the company may gain less profits than it would, for example, if the DH price is determined using the cost-plus method. As a result, it may lead to a lower interest in investment and maintenance, such as the electricity market in Sweden [11]. Furthermore, the DH market in reality is never the textbook competitive market as presumed in Economic theory, while a typical DH market is characteristically a natural monopoly (see the detailed discussion above). Therefore, the optimal allocation of resources cannot be achieved by simply pricing DH at its marginal cost, even in a deregulated market. Although a competitive market environment can be developed through bidding, it is almost impossible for bidders to bid according to their marginal costs, due to imperfect information, as well as the availability of alternative heating products [12, 13].

2.2 MARGINAL COST MODEL

The marginal cost (MC) has been commonly used for heat pricing in Sweden. In a marginal cost-based pricing model, the total price normally involves two parts: fixed cost and variable cost, as shown in Eq. 1.

$$MC = \frac{d(TC)}{d(Q)} = \frac{d(FC+VC)}{d(Q)} = \frac{d(VC)}{d(Q)} \quad (2-1)$$

where TC is total cost, FC is fixed cost, VC is variable cost and Q represents the volume of heat production. VC mainly consists of energy cost, labor cost and other variable operation cost, such as the cost for marketing. Energy cost or fuel cost can be calculated as:

$$Fuel\ cost = Fuel\ price + Sulphur\ tax + NOx\ tax + Carbon\ tax + Energy\ tax \quad (2-2)$$

For a DH system, heat can be produced in different ways, such as combined heat and power system, heat pumps and oil/gas/biomass boilers. Their operations are combined in order to meet dynamic heat demands in different weather conditions.

Different technologies have different investment cost and energy efficiencies, which further result in different operation costs.

According to Eq. 1, it is clear that FC is not really reflected by the marginal cost since it is considered as a constant. In order to reduce the financial risks due to the high investment cost, a fixed cost is usually added.

2.3 PRICE COMPONENT IN SWEDEN

The Swedish DH sector experienced a transition from a regulated to a deregulated market in the past decades. Prior to the deregulation of the DH market on January 1, 1996, all DH plants and distribution networks were owned and operated by Swedish municipalities. The DH companies were not allowed to make profits according to Swedish law [14]. After deregulation, many municipalities sold their DH companies to either the private sector or municipality- or state-owned large energy companies.

A survey has been conducted to investigate the current price models adopted by the REKO labeled DH companies in Sweden. More than 170 price models have been collected. A price model normally includes four components: fixed cost, capacity cost, energy cost and flow cost [15].

- Fixed cost is the fee that a user needs to pay each month for being connected to the network. 65% of investigated DH companies have such a fixed component in their price models.
- Capacity cost is charged to cover the cost of DH companies in order to maintain a certain level of capacity for users' peak demand, for instance, investment costs of facilities. It is common to classify it as a kind of fixed cost. The most primitive method (by 14% of investigated DH companies) is to use consumers' total consumption during a certain period of time (either the previous year or the previous high peak period) to determine their capacity needs. The most commonly used method (by 53% of investigated DH companies) is called Category-Figure method, which is an engineering approximation based on the primitive method, to differentiate different types of users. It gives different consumption time (category-figure) to different user groups and use it to determine the customer's required capacity.
- Energy cost, as the variable cost, is included in all of the price models. Primarily, 59% of DH companies use constant energy price. Seasonal energy price is used by 37% of DH companies, which means the energy price is more expensive in the winter time and cheaper during summer time. About 1% of DH companies set their energy price according to the outdoor temperature, which is generally a good indicator on the energy demand in the energy system and this information could also be accessed easily by the general public. About 2% of DH companies use subscribed energy scheme.
- Flow cost is, in principle, a cost charged on volume of hot water needed to deliver the energy user consumes. It is usually a good motivation for the user to improve the performance of their heat exchanger. But it is only adopted by 42% of DH companies

2.4 PRICING DILEMMA

- Fixed cost vs. variable cost

A DH company would have financial risks if its DH price is predetermined for a long time. A common way to reduce this financial risk is to divide the price into two parts: a fixed component and a variable component [16]. A pricing approach comprising a fixed component can reduce producers' risks caused by fluctuations in consumption. With the deregulation of the DH market, DH pricing is moving towards a more consumer-oriented approach, in terms of more flexible pricing options for consumers to choose. The main reason there is a preference for a fixed charge is that heat demand fluctuates largely over a year, and a high proportion of the operating costs of a DH system doesn't change in a short run. Therefore, a fixed charge can streamline the cash flow of producers.

The fixed charge usually covers the cost related to the investment cost. Therefore, it is common to link the fixed cost to the heat capacity of the users. However, on the contrary, consumers always prefer a high share of the energy cost, which can increase the flexibility of heat consumption and price transparency. This means that the pricing mechanism, especially the magnitude of the fixed component, should be decided to balance the needs of producers and requirements for consumers.

- Historic consumption vs. current heat demand

In order to improve the competitiveness of DH, nowadays, some DH companies are reforming their price models and the capacity cost receives the most attention. The purpose of changing the capacity cost is to encourage consumers to reduce their peak heat capacity and therefore DH companies can reduce the investment cost and production cost, which may lead to a lower heat price. The charge of capacity cost is usually determined according to the historical heat consumption data. However, the climatic condition changes year by year, resulting in a dynamic change of capacity. Even though a correction based on the normal year can be introduced, there could still be a big deviation in the determination of the heat capacity, because the yearly degree-day may not accurately reflect the peak heat capacity.

- Peak load vs. individual peak consumption

The intention of using capacity based pricing is to motivate the consumers to change their behaviors to reduce the peak load on a long-term basis. Unfortunately, this may not solve the problem of high peak loads in the system. Different consumers have different consumption profiles; and their individual peak consumption may not occur at the same time. Therefore, reducing the individual peak consumption may not really reduce the peak load.

- Complex price model vs. pricing transparency

There are a couple of methods to determine the heat capacity demand for charging the capacity cost. One is the assigned consumption hour method, which determines the capacity by dividing the customer's annual consumption by assigned consumption hours. The assigned consumption hour is a constant but

different for different types of customers. However, how it is obtained is not fully clear. In addition, the capacity cost is charged as capacity price multiplied by capacity, (e.g. a capacity price [SEK/kW] multiplied by capacity [kW]). The determination of capacity price is not easy to understand. It is commonly assumed that the income from the capacity cost accounts for 30-50% of total income.

2.5 NEED OF DYNAMIC PRICING MECHANISMS

As discussed above, the big concern coming from the high capital cost is the main driving force for charging a higher capacity cost in order to motivate consumers to reduce their peak consumption. However, due to the dynamic change of ambient temperature, the purpose may not be achieved in a short term. Meanwhile, charging a higher capacity cost doesn't contribute much to encourage consumers to save energy. From the perspective of strengthening sustainability, a good price model should be able to:

- Reflect the dynamic production cost accurately
- Motivate consumers to reduce the peak load and save energy at the same time
- Be predictable
- Be transparent and easy to understand

A dynamic pricing mechanism based on the prediction of system heat demand becomes more attractive with the above criteria in mind. Based on the demand prediction, DH companies could more accurately foresee the peak load and estimate the extra cost for covering the peak load. By charging a higher price for the peak, it should be possible to reduce the peak load. Since most of the heat productions are based on CHP, a dynamic heat price can also cope with the dynamic electricity price in a better way. The dynamic pricing model can also provide more transparent information to consumers, which has been proved to be an effective way to achieve energy savings in the domestic sector. By understanding the pricing mechanism, consumers can change their behaviors in order to reduce the heat consumption and save the cost.

3 Dynamic pricing mechanism

3.1 LEVELIZED COST OF HEAT

The levelized cost of energy is a popular methodology for evaluating the economic competitiveness of electricity generation technology over the long term [17]. This approach computes the average cost of energy production over the lifetime, taking into consideration main cost components, such as investment, operations and maintenance (O&M), fuel, and decommissioning costs. Different from the marginal cost model, in which the fixed cost is charged on a period basis, in the levelized cost of heat (LCOH) model, the fixed cost is embedded in regular DH prices. The investment of various types of technology is allocated over their life time and the cost components at a specific time point include the cost for the actual technologies in use. Therefore, there is no need to include those different cost components presented in Chp 2.3. The main advantage of the LCOH-based method lies in its flexibility and transparency; while the biggest challenge for calculating LCOH is how to estimate the heat production during the lifetime. LCOH-based prices are usually calculated on an hourly basis:

$$LCOH = LCOH_{fuel} + LCOH_{TIC} + LCOH_{O\&M} \quad (3-1)$$

$$LCOH_{TIC} + LCOH_{O\&M} = \frac{\sum_t (TIC_t + FOM_t + VOM_t) \times (1+r)^t}{\sum_t HEAT_t} \quad (3-2)$$

where TIC is the total investment cost, FOM and VOM are fixed operation & maintain cost and variable operation & maintain cost respectively, r is the interest rate, t is the life time and $\sum_t HEAT_t$ is the total heat production during the life time.

For different heat production technologies, LCOHs are different. The overall LCOH is calculated via combining LCOH for each technology according to their heat productions:

$$LCOH = \sum_{i=1}^n (LCOH_i \frac{Heat_i}{\sum Heat_i}) \quad (3-3)$$

3.2 LCOH FOR CHP

Since the CHP plant produces heat and power simultaneously, the fuel consumption should be allocated for between electricity and heat production, which directly affects the cost for heat production.

$$F_t^e = (1 - \alpha_h) \times Fuel \text{ cost} \quad (3-4)$$

$$F_t^h = \alpha_h \times Fuel \text{ cost} \quad (3-5)$$

where F_t^e and F_t^h are the fuel costs of electricity and heat respectively.

There are a number of principles used to allocate joint costs between heat and power for CHP plants [18]. There following three methods have been tested in this work:

(M-1) Setting the price of electricity, and then calculating the cost of heat accordingly. All fuel costs are allocated to heat. The income from selling electricity at the market price is deducted from the total cost.

(M-2) Allocating the costs in proportion to the amounts of generated heat and electricity. To simplify the calculation, it is assumed that electricity and heat are produced with the same efficiency in a CHP plant. Therefore, the total fuel costs can be divided into heat costs and electricity costs according to the electricity-to-heat ratio. Sweden applies this method to energy taxation on CHP plants.

(M-3) Allocating the costs in proportion to the exergy of the generated heat and electricity. Another way to consider the influence of efficiency is to use the concept of exergy, which reflects the quality of energy and can be calculated using the laws of thermodynamics. Since the product of electricity has higher exergy than the product of heat, this method will normally attribute a relatively large portion of the total costs to electricity generation.

As aforementioned, the fuel allocation should only be applied to the fuel that is used to product heat and electricity. However, in the CHP system, fuel is not always used for combined production as shown in Fig 3-1. For example, at a high heat demand, steam can bypass the turbine to produce more heat. The fuel used to produce bypass steam should not be allocated between heat and electricity, as it is used only for heat production. In order to accurately calculate the cost for both heat and electricity production, heat produced in the CHP system can be further divided into H_{CHP} and H_{HO} , which correspond to the heat produced in combination with electricity and the heat produced from bypass steam respectively. Meanwhile, extra heat can be recovered from FGC, which is usually released to the ambient and not included in the heat production of CHP. Therefore, the fuel of H_{FGC} can be ignored.

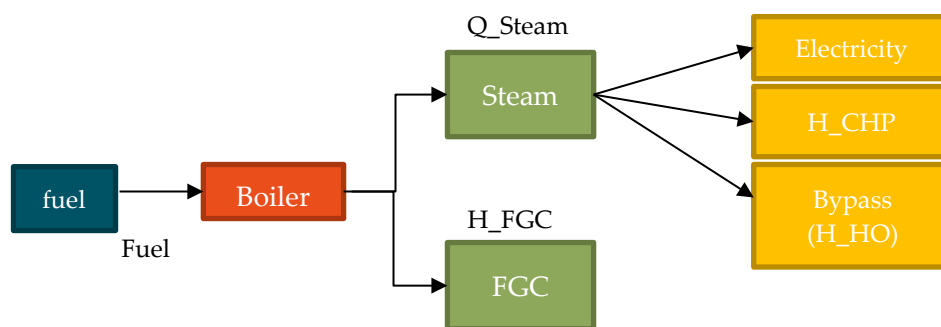


Fig 3-1 Energy flow in a CHP system

3.3 CASE STUDY

LCOH was calculated for a real DH system, which consists of a CHP plant, a biomass boiler, and a bio-oil boiler. Detailed input data and assumptions are listed in Table 3-1.

Table 3-1 Input data and assumptions

Parameter	Unit	Value
CHP Boiler	MWth	150
Steam turbine (ST)	MWe	39
Designed heat power ratio		1,82
Min partial load of ST	%	25
FGC	MWmax	32
Boiler efficiency	%	85
CHP TIC	MUSD	12,1
Operating hour of CHP	hr	7500
Biomass boiler	MWth	66
Biomass boiler TIC	MUSD	3,7
Bio-oil boiler	MWth	24
Bio-oil boiler TIC	MUSD	1,98
Lifetime	yr	20
Interest rate	%	8
Biomass price	USD/kWh	0,02
Electricity price	USD/MWh	2,9
Bio-oil price	USD/kWh	0,055
Profit	%	8

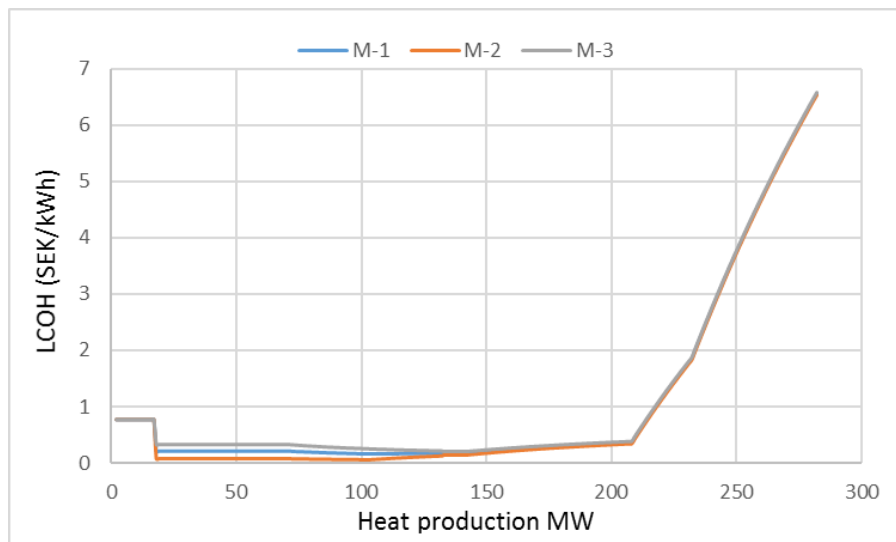


Fig 3-2 Overall LCOH of DH system

Figure 3-2 shows the calculated LCOH at different heat capacities. In general, LCOH increases along with the increase of heat capacity no matter which model is used to allocate the fuel cost. CHP, which is normally provides the base load, has low production cost; on the contrary, the biomass boiler and bio-oil boiler, which are used to cover the peak load, have relatively high production costs. The high LCOH at very low heat capacity is mainly due to that at a demand lower than 25%

of CHP capacity, CHP is not in operation. Instead, biomass boiler is used. Meanwhile, the high LCOH of biomass and bio-oil boiler primarily comes from the short operation hours, which results in a high fraction of TIC in LCOH. For bio-oil boiler, the high LCOH is also owing to the high fuel cost.

Fig 3-3 shows the calculated LCOH for CHP. Different methods, which are used for allocating the fuel cost for productions of power and heat, result in different LCOH_CHP. In general, there is a clear drop for all methods when FGC is introduced in heat production. This is mainly due to that the heat produced from FGC doesn't require extra fuel. Therefore, when the cost remains the same, producing more heat gives a lower production cost. For M-1 and M-2, LCOH goes up when bypass is introduced. This is owing to more fuel allocated for heat production as electricity production is less. For M-3, due to the high fraction of the capital cost in LCOH, H_CHP has a higher cost than H_HO. Therefore, when less heat is produced from CHP and more heat is produced from bypass, LCOH_CHP decreases.

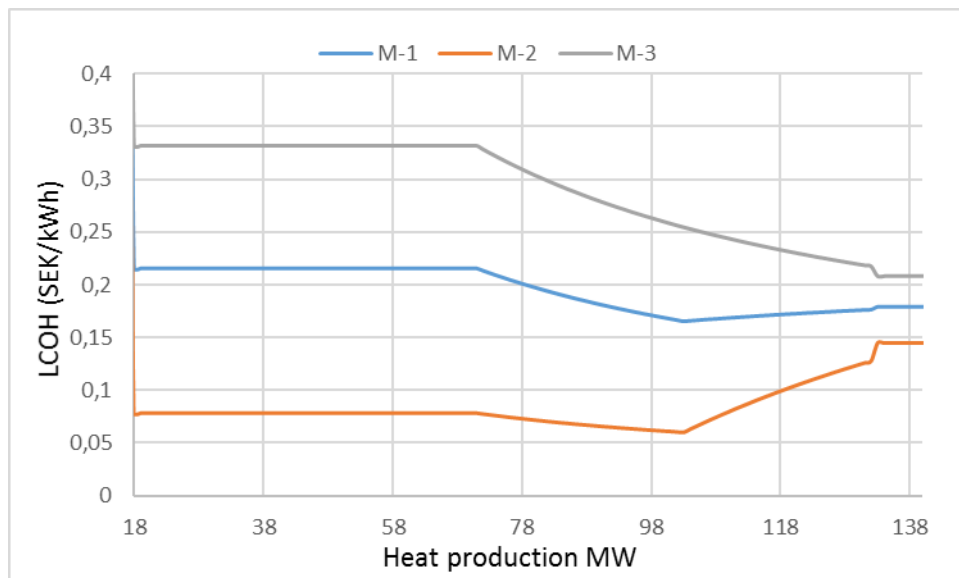


Fig 3-3 LCOH of CHP

Based on LCOH, dynamic heat price can be obtained at dynamic heat demand by adding a profit in LCOH. During July 20 to Aug 20, CHP is assumed to be shut down for maintenance, and the biomass boiler is usually used as an alternative. Fig 3-4 compares the prices from different price models at different heat demands. Old PM and New PM are two real price models, which are based on seasonal fuel cost and subscribed heat capacity [15].

Different from the LCOH methods above, district heating companies use another approach in their daily practice. According to an earlier price model survey [15], they allocate more than 95% of their income in two different components based on their cost structure: the Energy Demand Component (EDC) and the Load Demand Component (LDC).

The EDC is used to cover the production cost of district heating, which is mainly the cost of fuel, taxes and operating costs, which charges district heating user a certain amount for each kWh of heat consumption.

LDC is used to cover the cost to the district heating company to maintain a certain level of capacity for users' peak demand, e.g. for investment costs of facilities, etc. Since the capacity reserved for a specific user is related to the user's peak demand, district heating companies usually set a price for each kW of peak demand (usually in SEK/kW), and use user's peak demand as a parameter to charge users.

- Old PM (Seasonal Price model)

One of the commonly used price model is the seasonal price model, this model has a LDC based on users' highest measured daily average demand in one year, and a two-level seasonal energy price (higher during winter and lower during summer) in EDC to differentiate consumptions in different period.

Under this model, a user's district heating cost is expressed as:

$$E = P_{energy.w} \times C_w + P_{energy.s} \times C_s + P_{load} \times L_{peak} \quad (3-6)$$

$P_{energy.w}$: Energy price during winter season, SEK/kWh.

$P_{energy.s}$: Energy price during summer season, SEK/kWh.

C_w : User's winter district heating consumption, kWh.

C_s : User's summer district heating consumption, kWh.

P_{load} : Load demand price, SEK/kW.

L_{peak} : User's peak demand (daily), kW

- New PM (Subscription Price Model)

Other than the commonly used Seasonal Price Model, there are several newly emerged price models been adopted by large district heating companies such as Fortum in Stockholm. Similar to the seasonal price model, the LDCComponent in this model is also based on the peak demand of users, except in hourly basis. The EDC, on the other hand, is based on users instant demand level: the district heating company suggests a subscription level in proportion with the user's peak load demand, users are entitled to pay a lower price (so called base price) for their energy consumption below the subscription level (base load); however, peak energy consumption above the subscription level is charged at a higher price (so called peak price).

User's cost is calculated using the formula below.

$$E = P_{energy.b} \times C_b + P_{energy.p} \times C_p + P_{load} \times L_{peak} \times \alpha \quad (3-7)$$

$P_{energy.b}$: Base energy price (subscribed part), SEK/kWh.

$P_{energy.p}$: Peak energy price (exceeded part), SEK/kWh.

C_b : User's base load, kWh.

C_p : User's peak load, kWh.

P_{load} : Load demand price, SEK/kW.

L_{peak} : User's peak demand (hourly), kW

α : the subscription level, proportion of base load plant's capacity compared with system's total capacity, %.

Table 3-2 Price-levels of Price Models in use

Seasonal Model	
Price level for Energy Demand Component in summer (SEK/kWh)	0.253
Price level for Energy Demand Component in winter (SEK/kWh)	0.455
Price level for Load Demand Component (SEK/kW)	560
Subscription Model	
Price level for Energy Demand Component base (SEK/kWh)	0.369
Price level for Energy Demand Component peak (SEK/kWh)	1.386
Price level for Load Demand Component (SEK/kW)	729

Both Old-PM and New-PM are not dynamic price models. To generate the hourly price for the real price models, 638 user's consumption data has been used in the calculation. Each user's hourly costs on EDC are calculated according to the energy consumption and the energy price level during that hour. The annual cost on LDC is first calculated based on the user's peak demand and the load price level, and then evenly distributed into each hour of the year. The average hourly price then is calculated by adding up each user's hourly cost on both EDC and LDC and then divided by the total consumption.

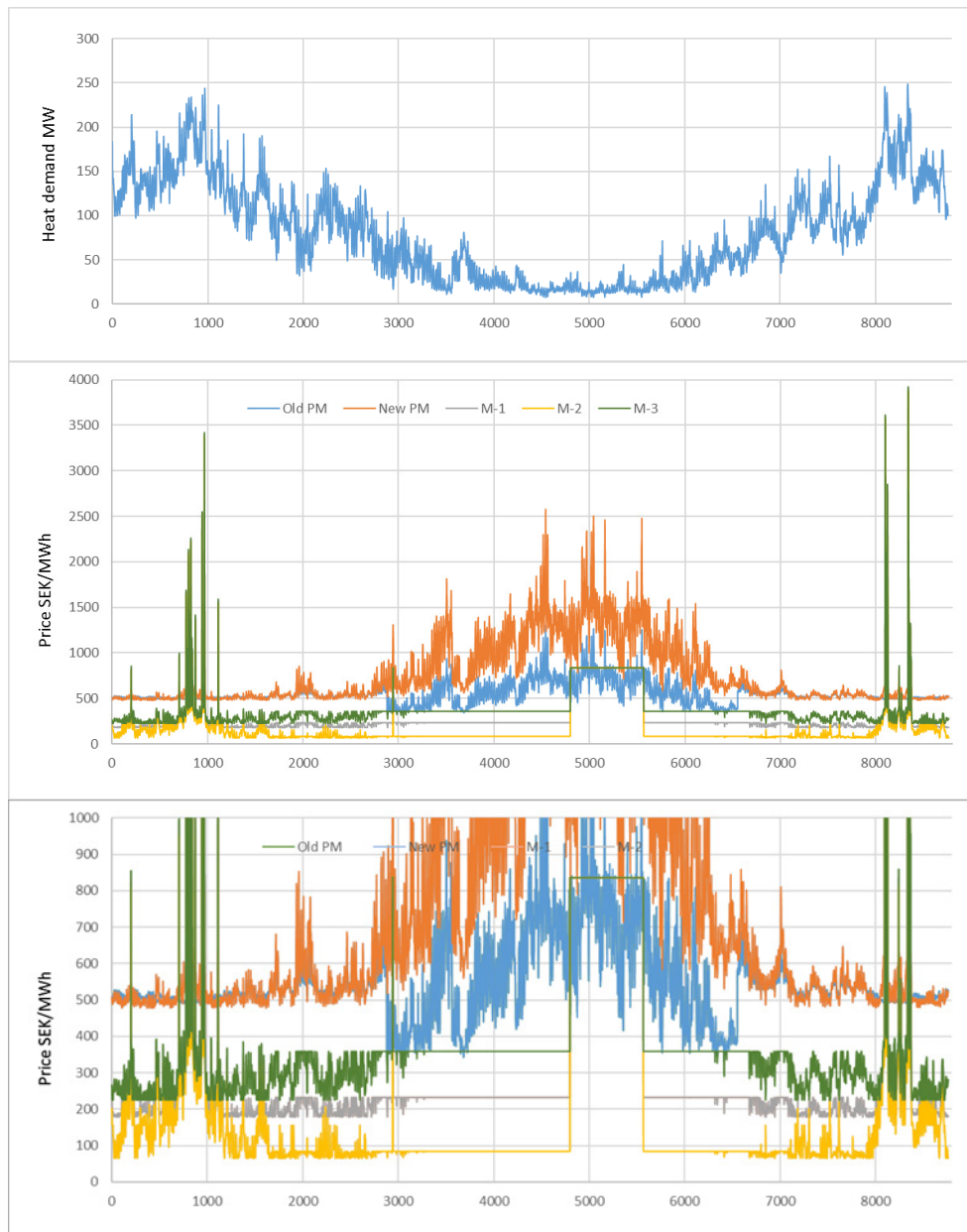


Fig 3-4 Heat price from different price models at different heat demands

It is clear that the prices based on LCOH are much lower than those from the real price models, which implies there should be a potential to lower the heat price. Meanwhile, LCOH can reflect the variation of heat demand in a better way and effectively cover the high cost at the peaks. It is also interesting to see that the prices at low heat demands, for example in summer, are still quite high. For the dynamic model based on LCOH, since CHP is shut down during summer and biomass boilers are used instead, the high fuel cost results in a high price. Meanwhile, for the two real price models, the high price during summer time is majorly due to the fixed LDC, which is not allocated according to the energy consumption but allocated based on time. That means the cost of LDC is a constant value in each hour, to calculate the average price for each kWh energy

consumption, it has to be divided by the total consumption. So when the consumption is very low, this part will contribute a lot to the average price. This might seem abnormal but is reasonable for the energy company, because when they set up the price, it is impossible to foresee how much energy they are going to sell, and the maintenance is more or less irrelevant to the total consumption. Hence to allocate this part of cost into energy consumption means higher risk, so if allocate these fixed costs into energy consumption, they are kind of forced to raise the price to cover the possible risk (even though a higher profit is not even the main goal here).

3.4 MODEL COMPARISON

Table 3-3 compares the characters of different price models. In general, the price model based on seasonal fuel cost is simple to understand. As the fuel cost accounts for the major part of the heat price, it can also reflect the dynamic production cost. For the price model based on subscribed heat capacity, it is largely determined the peak demand of the customers. Therefore, it can effectively motivate customers to reduce the peak load. Nevertheless, such a model is difficult to understand and is less transparent. For the price model based on LCOH, the price varies with the production cost, which is further determined by the demand; hence, it can motivate customers to reduce the heat consumption, especially during the peak time. It is also easy to understand but its complexity of calculation results in big uncertainties of the cost.

Table 3-3 Characters of different price models

	Seasonal fuel cost (e.g. Old PM)	Subscribed heat capacity (e.g. New PM)	LCOH based PM (e.g. M-1, M-2, and M-3)
Simplicity	++	-	-
Predictable	-	-	+
Transparent	+	--	+
Reflecting the dynamic production cost	+	+	++
Reflecting the dynamic heat demand	--	-	++
Motivate consumers to reduce the peak load	-	++	++
Motivate consumers to save energy	+	-	++

4 Prediction of the total heat demand

In general, there are two types of models used for predicting the heat demand: physical models, which calculate the heat loss based on the principle of heat transfer; and statistic models, which correlate the demand to some factors, such as weather data, based on large amount of metering data. Evolving technologies about smart meters and smart energy network open up new opportunities, allowing energy companies to do things in a better way or do things they never could before, such as better understanding customer segmentation and behavior, shaping customer usage patterns, improving the reliability, optimizing unit commitment and more [19]. Hence, with the development of heat metering, the statistic models attract more and more attention in the prediction procedure, due to its ability to reflect the sociological parameters such as consumer behaviors. For example, ANN models, one type of statistic models, have been used to predict the heat demand and shown the ability to produce accurate predictions [20].

4.1 MODEL DESCRIPTION

A model based on Elman neural networks (ENN) was developed to predict the heat demand. Elman neural network [21-22], initially proposed for speech processing problem in 1990 by J. L. Elman, is a global feed forward local recurrent neural network. An ENN generally comprises four levels: the input, the hidden, the context, and the output layers. The structures of input, hidden, output layers are similar to normal feedforward neural network. The role of context layer nodes is to store the output values of the hidden layer nodes, which is equivalent to the time delay operator or the state feedback [23-24]. The model of Elman neural network is represented as follows:

$$x_1(k) = f[w^1 u(k-1) + w^{c1} x_{c1}(k)] \quad (4-1)$$

$$x_i(k) = f[w^i x_{i-1}(k-1) + w^{ci} x_{ci}(k)], i = 2, 3, \dots, s \quad (4-2)$$

$$x_{ci}(k) = x_i(k-1), i = 2, 3, \dots, s \quad (4-3)$$

$$y(k) = g[w^{s+1} x_s(k)] \quad (4-4)$$

where s is number of hidden layers, $u(k)$ is the input of the model, $x_{ci}(k)$ and $x_i(k)$ are the output of context layer i and hidden layer i , $y(k)$ is the output of output layer, w^1 is the connection weight matrix between the input layer and the hidden layer 1, w^i is the connection weight matrix between the hidden layer i and the hidden layer $(i-1)$, w^{n+1} is the connection weight matrix between the hidden layer n and the output layer, respectively, w^{ci} is the connection weight matrix between the hidden layer i and the context layer i . $f(\cdot)$ and $g(\cdot)$ are transfer functions, $f(\cdot)$ is usually sigmoid, tangent sigmoid or logarithm sigmoid transfer function, and $g(\cdot)$ is usually a linear transfer function. The structure of ENN with multiple hidden layers is shown in Fig 4-1.

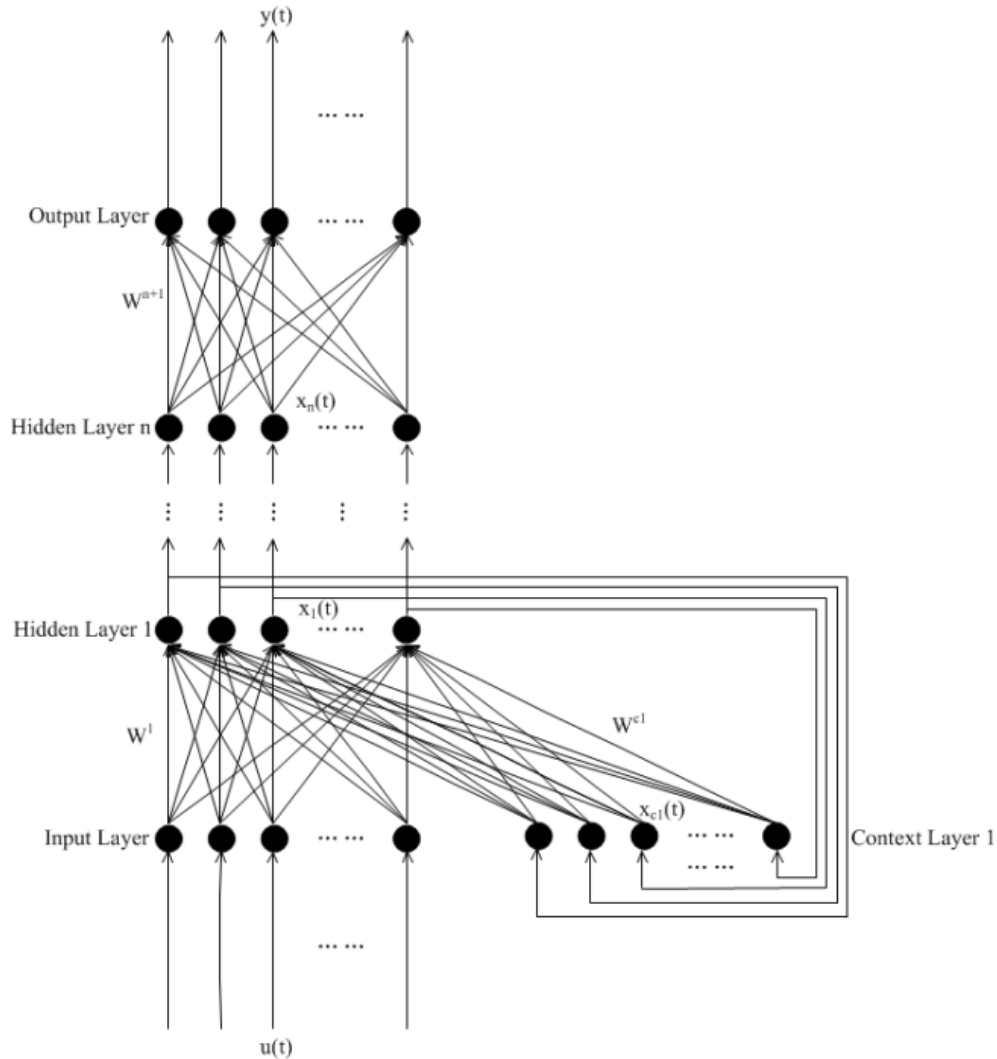


Fig. 4-1. The structure of a typical Elman neural network (ENN)

To investigate the impact of the length of slide window on heat demand prediction, data in consecutive 2, 4 and 8 hours are combined to create a super-vector, respectively. A step size, which is set as a half of the length of slide window, is selected to update the super-vector. For example, if 4 hours is chosen as the length of slide window, then the step size will be 2 hours, the first super-vector will contain the data from 1st to 4th hours and the second super-vector contains the data from 3rd to 6th hours. To investigate the impact of the number of hidden layers in ENN on heat demand prediction, 4 and 8 layers are selected as the number of hidden layers.

The training steps of ENN are as follows [25]:

$$\begin{cases} \Delta w_{ij}^{s+1} = \eta_{s+1} \delta_i^{s+1} x_{sj}(k) & i = 1, 2, \dots, m; j = 1, 2, \dots, n \\ \Delta w_{jl}^p = \eta_p \delta_j^p x_{pj}(k) & j = 1, 2, \dots, n; l = 1, 2, \dots, n; p = 2, 3, \dots, s \\ \Delta w_{jq}^1 = \eta_1 \delta_j^1 u_q(k-1) & j = 1, 2, \dots, n; q = 1, 2, \dots, r \\ \Delta w_{jl}^{cp} = \eta_{cp} \sum_{i=1}^m (\delta_i^{p+1} w_{ij}^{p+1}) \frac{\partial x_{pj}(k)}{\partial w_{jl}^{cp}} & j = 1, 2, \dots, n; l = 1, 2, \dots, n; p = 2, 3, \dots, s \end{cases} \quad (4-5)$$

$$\delta_j^p = \sum_{i=1}^m (\delta_i^{p+1} w_{ij}^{p+1}) f'_i(\cdot), p = 1, 2, \dots, s \quad (4-6)$$

$$\delta_i^{s+1} = (y_{d,i}(k) - y_i(k)) g'_i(\cdot) \quad (4-7)$$

$$\frac{\partial x_{pj}(k)}{\partial w_{jl}^p} = f'_i(\cdot) x_{li}(k-1) + \alpha \frac{\partial x_{pj}(k-1)}{\partial w_{jl}^p} \quad j = 1, 2, \dots, n; l = 1, 2, \dots, n; p = 2, 3, \dots, s \quad (4-8)$$

where η_p and η_{cp} ($p = 1, 2, \dots, s+1$) are the training steps of w^p and w^{cp} , m is number of the output layer nodes, n is number of the hidden layer nodes, r is number of the input layer nodes, and s is number of the hidden layers.

The Z-Score or named standard score is used as the normalization method before training step to preprocess measured data and represented as follows:

$$\hat{x}_i = \frac{x_i - E(x)}{\sqrt{D(x)}}, i = 1, 2, \dots, n \quad (4-9)$$

$$E(x) = \frac{1}{n} \sum_{i=1}^n x_i \quad (4-10)$$

$$D(x) = \frac{1}{n-1} \sum_{i=1}^n (x_i - E(x))^2 \quad (4-11)$$

where x_i is an element of $x = (x_1, x_2, \dots, x_n)$ which is the measured data, $\hat{x}_i$ is an element of $\hat{x} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$ which is the normalized data, $E(x)$ and $D(x)$ are the sample mean and the unbiased sample variance of x , n is length of x and $\hat{x}$.

To evaluate the model performance, the mean absolute percentage error (MAPE), which is defined as Equ 4-12, as indicator:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - y_{pi}|}{y_i} \times 100\% \quad (4-12)$$

Maximum absolute deviation (MAD) is another important indicator, which is defined as:

$$MAD = \text{Max} \left(\frac{|y_i - y_{pi}|}{y_i} \times 100\% \right) (i = 1 \dots n) \quad (4-13)$$

4.2 KEY INPUT FACTORS

Statistic models need to correlate heat demand to some parameters, such as weather conditions, building type and time of the day [26] etc. The ambient temperature is the most important weather condition, since it determines the temperature difference between indoor and outdoor, which is a key driving force for heat transfer [27-28]. However, it is not sufficient to obtain satisfying results by considering only ambient temperature. In order to further improve the accuracy of prediction, existing studies have tried to consider other weather conditions in predictions, such as wind speed and direct solar radiance. For example, Michalakakou et al. involved direct solar radiance as one of the inputs in an artificial neural network (ANN) model to forecast the heat demand in residential

buildings [29]. Unfortunately, the effect of direct solar radiance on the prediction of energy consumption was not carefully examined. Yang et al. combined the numerical weather prediction (NWP) with an ANN model for the projection of heat load, in which both direct solar radiance and wind speed were taken as inputs [30]. Kusiak et al. identified wind speed as an important parameter in predicting building energy demand [31]. Fu et al. verified the importance of direct solar radiance on the thermal load of a micro DH network [32]. In contrast, there are also researchers who argued that wind speed could be ignored in the prediction of heat demand [33-35]. In general, existing studies have recognized the effects of wind speed and direct solar radiance on the heat demand of buildings, while their specific impacts on heat demand in buildings have not been extensively examined, especially in a quantitative way. In order to achieve a high accuracy of prediction, the parameter that has a greater impact on the heat demand should be given a higher priority in the model. Therefore, the impacts of direct solar radiance and wind speed on heat demand in buildings are compared in order to identify the most important parameters.

Hourly measured data during the period 2008-2011 were collected from a utility company, including heat demand, ambient temperature, direct solar radiance, and wind speed. Short term and long term predictions of heat demand were implemented to investigate the performance of ENN. In short term predictions, the data from October 2008 to February 2009 (five months) were used for model training and those on March 2009 (one month) were used for model validation. In long term predictions, the data in 2010 (one year), from 2009 to 2010 (two years) and from 2008 to 2010 (three years) were used for model training and those in 2011 (one year) were used for model validation. Due to the difference of heat demand in working day and non-working day, this work focuses on working days only in order to achieve a higher accuracy.

To evaluate the impacts of wind speed and direct solar radiance on the prediction of heat demand, respectively, four datasets were created for Elman neural network training, which details are listed in Table. 4-1.

Table 4-1. Dataset description

	Heat demand	Ambient temperature	Direct solar radiance	Wind speed
Dataset A	√	√	×	×
Dataset B	√	√	√	×
Dataset C	√	√	×	√
Dataset D	√	√	√	√

The ENN model is trained by the data about the total heat production from 2008 to 2010, based on which dataset A, dataset B, dataset C or dataset D are extracted. Correspondingly, four ENN models are obtained, which are renamed as ENN-A, ENN-B, ENN-C and ENN-D. They used temperature, temperature and the direct solar radiance, temperature and the wind speed, and temperature, the direct solar radiance, and the wind speed as inputs respectively. Fig 4-2 compares the measured and predicted heat demand (in MW), and Table 4-2 lists the

corresponding MAPE and MAD. According to the results, all models are capable to reflect the change of heat demand and predict the heat demand with MAPE less than 6.6%, of which ENN-D shows the best accuracy with MAPE=6.35%. It is also clear that the introduction of direct solar radiance and wind speed has positive impacts on the performance of Elman neural network as ENN-B, C and D have smaller MAPE than ENN-A. Comparatively, the inclusion of wind speed results in a better prediction accuracy than that of the direct solar radiance. This implies that wind speed is a more important parameter. Meanwhile, the introduction of both wind speed and direct solar radiance simultaneously can further improve the model accuracy. Table 4-2 also presents the maximum absolute deviation (MAD) of different models. It is clear that compared to ENN-A, including direct solar radiance and wind speed can reduce MAD. Meanwhile, including direct solar radiance is more effective than including wind speed to reduce MAD, even though including wind speed (ENN-C) can result in a lower MAPE.

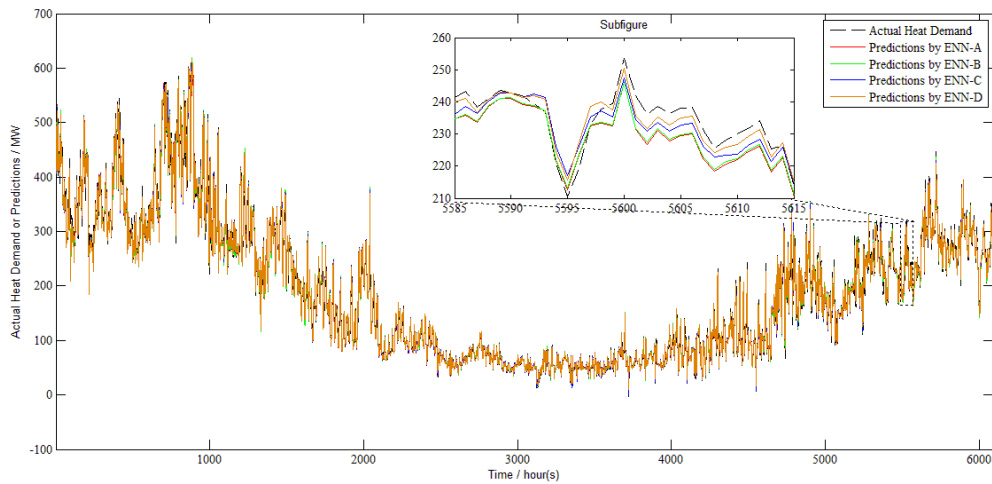


Fig. 4-2 Measured and predicted results (in MW) of the total heat demand

Table 4-2. MAPE and RMSE of different models

Model	MAPE	MAD
ENN-A	6.50%	91.6261
ENN-B	6.47%	71.8131
ENN-C	6.43%	81.5368
ENN-D	6.35%	70.6640

Fig 4-3 shows the distribution of absolute percentage errors. For all models, the most of errors (>74%) is between -5%~5%. However, it is worth to note that although ENN-A has the highest MAPE, it has the most points in the range of -5%~5%. Meanwhile, there are more points which heat demand was under-estimated than those which heat demand was over-estimated for all of the models.

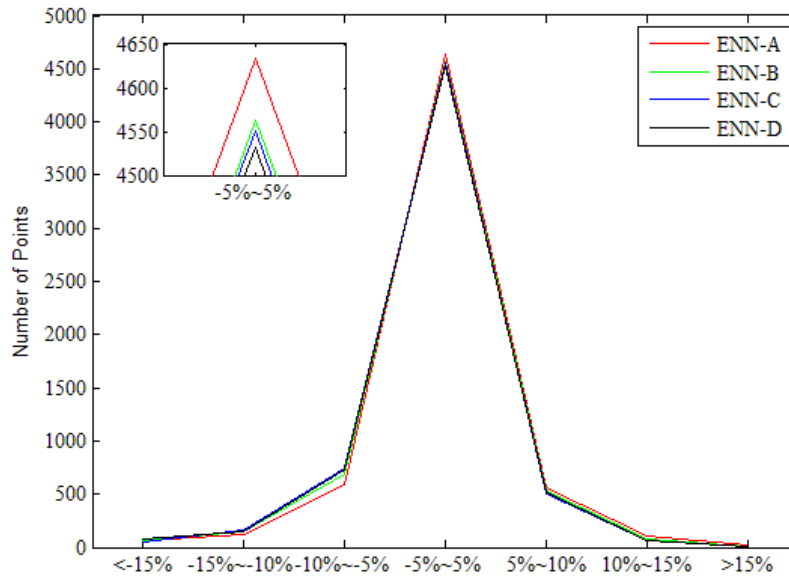


Fig. 4-3 Distribution of absolute percentage errors

In order to further understand the error distributions, MAPE and MAD of different models were also calculated at different heat demands and results were listed in Table 4-3 and 4-4. For all of models, MAPE decreases, while RMSE increases with the increase of heat demands. However, direct solar radiance and wind speed may have different influences at different heat demands. According to Table 4-3, as very low demand (0~150MW), it is more beneficial to include wind speed (ENN-C); while in the demand of 150~300MW, including direct solar radiance (ENN-B) has the lowest MAPE. In addition, despite that ENN-D has the lowest overall MAPE, it doesn't always have the lowest MAPE at different heat demands, actually it only has the lowest MAPE in the demand range of 300~450MW.

Table 4-3. MAPE of different actual heat demand ranges

heat demand (MW)	ENN-A	ENN-B	ENN-C	ENN-D
0~150	8.95%	8.87%	8.73%	8.83%
150~300	4.95%	4.93%	5.06%	4.97%
300~450	4.14%	4.13%	4.06%	4.04%
>450	3.89%	3.71%	3.63%	3.66%

Table 4-4. MAD of different actual heat demand ranges

heat demand (MW)	ENN-A	ENN-B	ENN-C	ENN-D
0~150	28.5977	26.4968	26.5604	23.7552
150~300	46.4071	55.1570	52.5413	54.5364
300~450	91.6261	71.8131	81.5368	70.6640
>450	48.5284	43.9760	46.3392	47.8068

The influence of parameters on MAD is not consistent at different heat demands. As illustrated in Table 4-4, including direct solar radiance can reduce MAD except in the demand range of 150~300MW and it is more effectively than including wind

speed. Moreover, similar to the results about MAPE, including both direct solar radiance and wind speed does not necessarily result in the lowest MAD.

The distribution of absolute percentage errors was also broken down at different heat demands and shown in Fig 4-4. Obviously, no matter what the heat demand is, the most of errors of all models are in the range of -5%~5%, which is similar to the overall error distribution. Comparatively, for the heat demand of 0~150MW, the fraction of the points with errors larger than 10% or lower than -10% is much higher. That is the reason that all models have the worst MAPE.

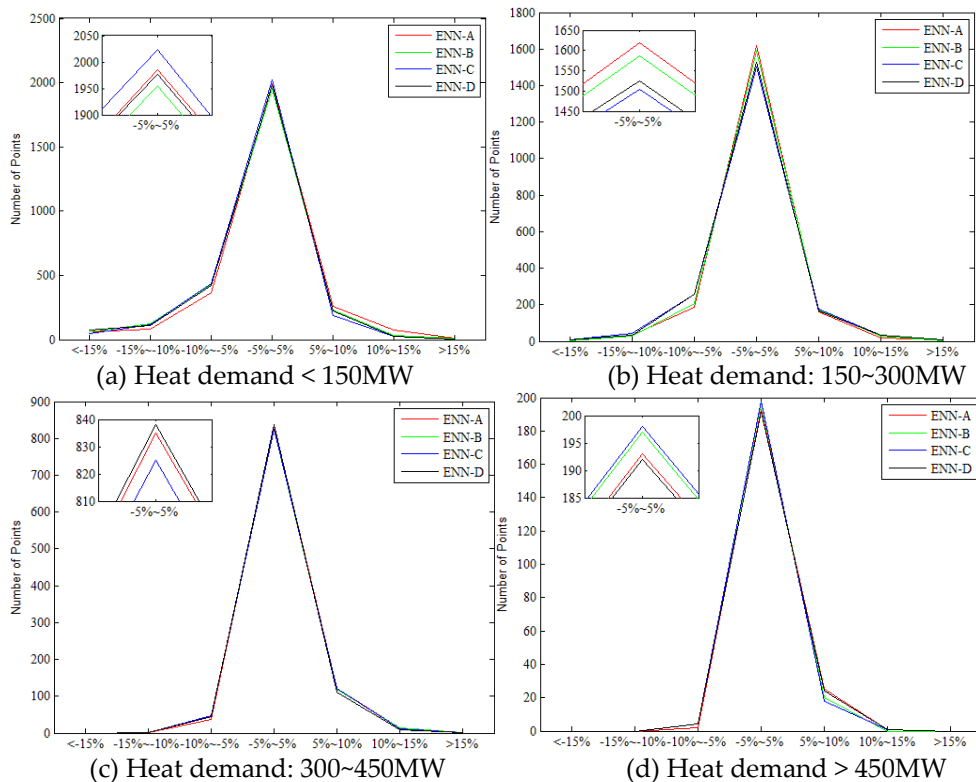


Fig. 4-4 Distribution of absolute percentage errors at different heat demand

As shown in Table 4-3 and 4-4, ENN may not benefit from the introduction of both wind speed and direct solar radiance simultaneously. This might be due to the following reasons: 1) the effect of one factor is already included into the other one (e.g., the effect of wind on the demand is reflected by the temperature), hence, it is not necessary to include redundant information in the analysis. This should be verified further in the future; 2) For ENN, there are different ways when integrating multi-factors. In order to further improve the ENN, advanced fusion methods may be applied. For example, with the principle of hierarchical neural network, two ENNs, each one with a single factor, can be trained separately. Then the two trained ENNs can be combined to get an ENN model for prediction.

4.3 DISCUSSION

It has been well recognized that heat demand is affected by social behaviors obviously. In our previous work, we noticed that the heat demand in summer isn't really affected by the ambient temperature, as shown in Fig 1, which implies that it is strongly affected by social behaviors. In order to consider the customers' behavior accurately, other parameters rather than climatic parameters should be included. For example, Dotzauer [32] constructed a model based on the premise that heat demand is affected by outdoor temperature and different consumer behaviors, which are tightly related to the time in a day. We also investigated the impacts of building type on the prediction of heat demand and found that categorizing buildings according to their functions represents a more effective way to improve the model performance. Nevertheless, the current classification of buildings is mainly done according to the function of building. Little work has been done about user clustering according to heat demand.

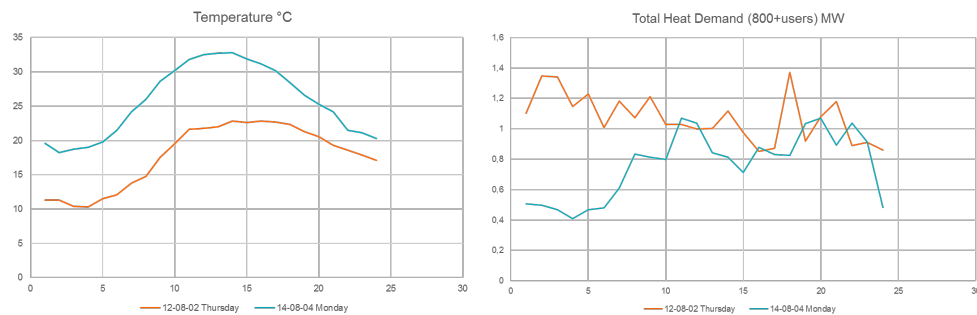


Fig 4-5 Impacts of social behaviors on heat demand in summer

Data corruption about heat demand has already been identified from our previous work, as shown in Fig 4-6. Abnormal data points have been found from both the production side (as shown in Fig 4-6(a)) and the consumer side (as shown in Fig 4-6(b)). Along with the development of smart metering technologies, more and more data become available; hence, there is an urgent need to develop a method that can cleanse the heat demand/production data systematically. However, no work has been done about data cleansing regarding heat demand. The data quality has been the bottleneck for developing more accurate models.

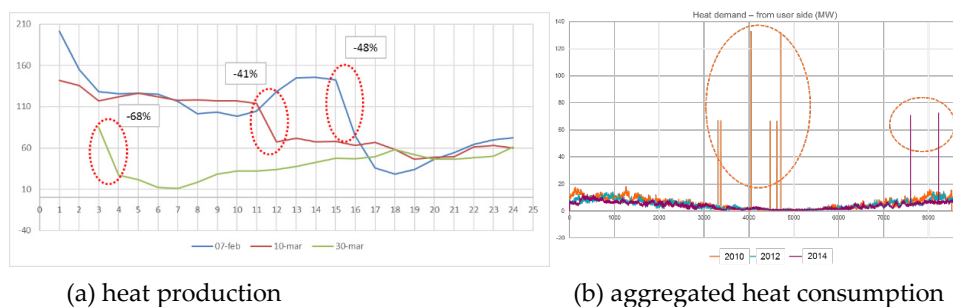


Fig 4-6 Abnormal data examples

5 Influences of new price model

Price model reforming could lead to a significant change in the expense of customers. It can also affect the selection of energy saving measures. In this chapter, the influences of the two real price models introduced in Chp 3 and the dynamic price model based on LCOH are compared.

5.1 INFLUENCES ON CONSUMERS

Fig 5-1 shows the heat demand and expenses under different price models for a typical customer of multi-family house. In general, the expense changes with heat demand no matter which price model is applied. For the two real price models (Old PM and New PM), since both models include the energy component, when the heat demand varies, the cost also varies. For the dynamic models based on LCOH, the cost is related to the heat demand more closely, hence, the expenses vary with the demand more obviously.

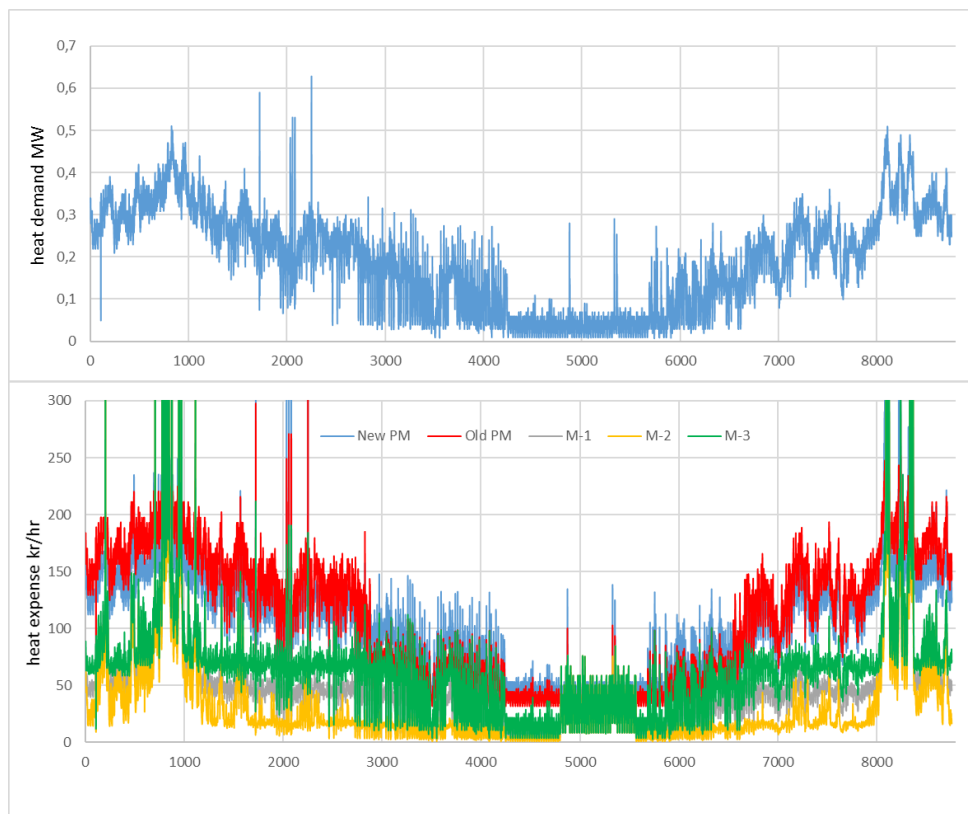


Fig 5-1 heat demand and expenses of a typical customer of multi-family house

From Fig 5-1, it is also clear that in most of the cases, the expenses calculated with the dynamic price model are lower than those calculated with the real price models. It implies that there could be a big potential to further lower the price. However, it should also be noted that even though the labor cost and profit have

been considered in the dynamic model, due to lack of detailed real data, there may be a big deviation from the assumed values, which can also result in a big difference. Nevertheless, for the peak demand, dynamic price models result in a higher cost than the real price models, and the difference is bigger at a higher peak load. Comparing the new PM and the old PM shows that introducing an hourly capacity load component results in a higher expense at higher heat demand, for example in winter; while a lower expense at a lower heat demand, for example in summer.

For other types of users, such as Office&school, Commercial buildings, Hospital&social buildings and industry, the influence of price models is quite similar.

5.2 INFLUENCES ON SELECTING ENERGY SAVING MEASURES

Three alternative solutions are considered in this study: using direct electrical heating (DEH) to provide the peak heating demand combined with DH covering base demand; installing heat pump (HP) to cover base demand combining with DH or DEH to provide peak demand, Fig 5-1 shows the consumption profile of each alternative. The annual cost of each solution is the sum of DH cost, electricity cost and annual investment cost for HP installation.

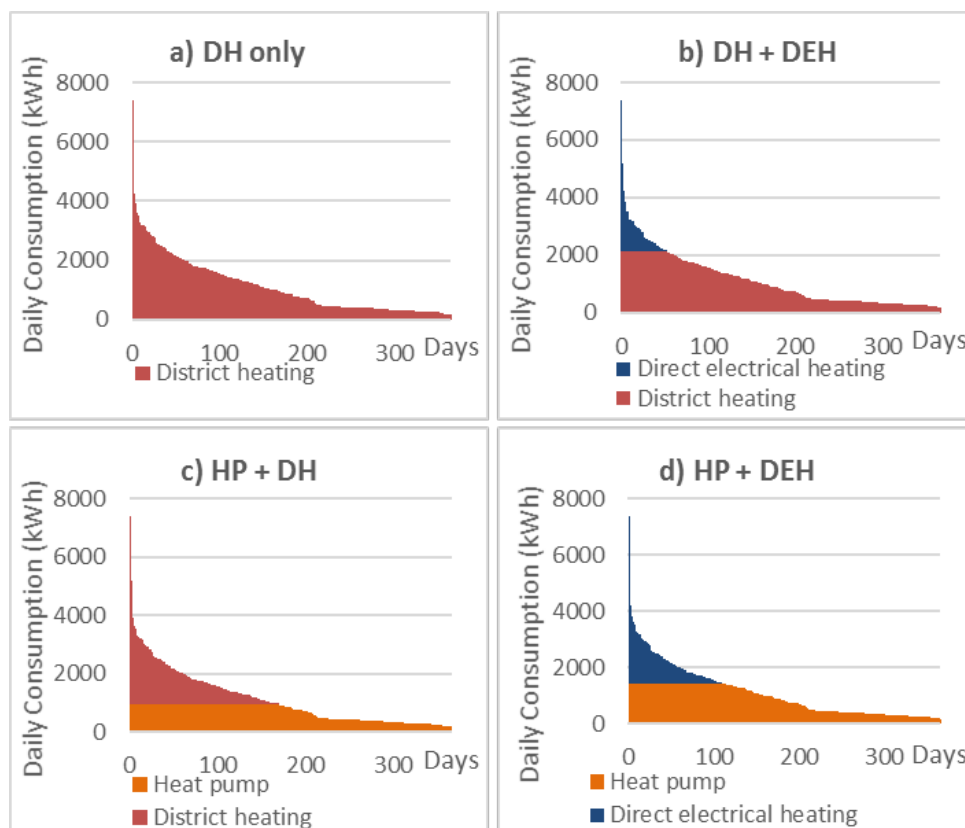


Fig. 5-2 Consumption profile of different heating solutions

The capacity of heat pump is dimensioned to achieve the optimistic annual cost in each solution that involves heat pump. The capital investment of heat pump is presumed to be €1580/kW per installed capacity [36], lifespan is 20 years, and interest rate is 5% [37]. The annual investment cost of heat pump could be calculated using Eq. 1, the result of annual investment cost is €157/kW · year per installed capacity. The SCOP of heat pump is assume to be 3.5. Price of electricity is €84/MWh [38]. The cost of implementing direct electrical heating equipment is presumed to be near zero compared to lifespan of 20 years.

$$C_{annual} = \frac{I_{cap} \times a^L}{L} \quad (5-1)$$

C_{annual} : Annual investment cost per installed capacity of heat pump, €/kW · year.

I_{cap} : Capital investment of heat pump, €1580/kW.

a : interest rate of capital, 3.5%/year.

L : Lifespan of heat pump, 20 years.

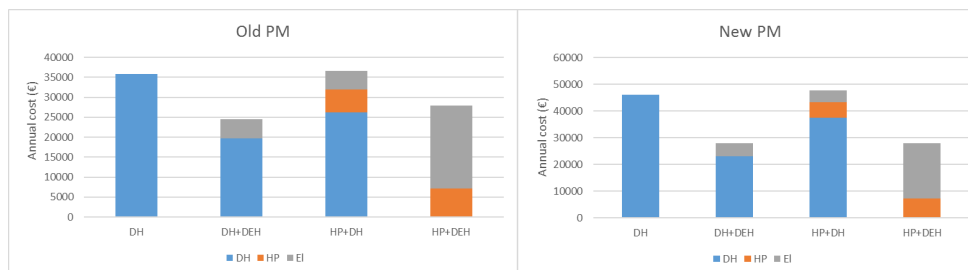
The annual heating cost of a vulnerable user is calculated by using different price models. Cost of three alternative solutions are calculated based on the same user's consumption pattern and a serial of technical assumptions. A DH user facing significant cost increase in the price model restructuring process was chosen according to our previous study [15] for the cost calculation. The annual costs of each alternative under different price models are illustrated in Figure 5-3 and Fig 5-4.

Firstly, the old-PM and new-PM are compared. Both consist of a Load Demand Component and an Energy Demand Component. Load demand component of old-PM charges user €59/kW for user's peak load demand in daily average, energy demand of old-PM is divided into two price levels: a lower price for energy consumption between May and September and a higher price (€48/MWh) for the rest of time. New-PM uses a subscription level in both load demand and energy demand level: user pays €77/MW for subscribed load demand (equals to 60% of user's peak load demand in hourly average), for energy demand under the subscription level, user pays a lower price (€39/MWh) for energy consumption under the subscription level and higher price (€146/MWh) for consumption over subscription level.

According to Fig 5-3(a), for the old PM, reducing the peak district heating load demand with direct electrical heating is the most economical alternative, which is 31% cheaper than district heating under old-PM. Installing a heat pump and using direct electrical heating to cover the peak demand is the second best choice, which could reduce the annual cost by 22%. Installing heat pump to supply base demand and using district heating to cover the peak demand is not much different from stick with district heating, which even increases the cost by 2%.

The rank of alternative solutions under new-PM is not exactly same as that under old-PM, as shown in Fig 5-3(b): heat pump combined with direct electrical heating becomes the most economical solution, which reduces the cost by 39,2%. It is slightly better than using direct electrical heating to cover the peak demand of district heating, which could reduce 39% of annual cost. Installing heat pump to

cover the base demand instead of district heating cannot achieve a cost reduction yet, which increases the cost by 3,6%.

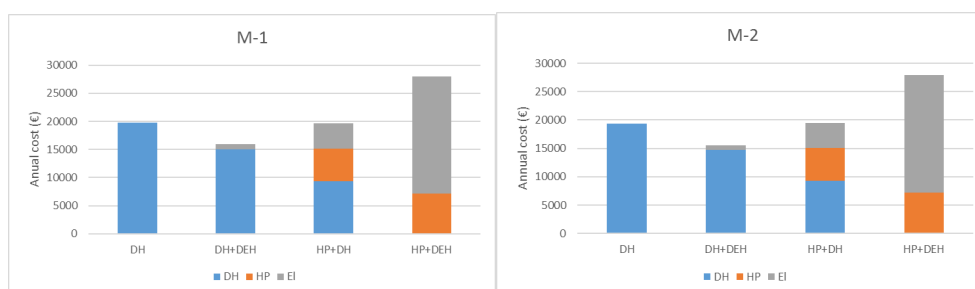


(a) Old-PM

(b) New-PM

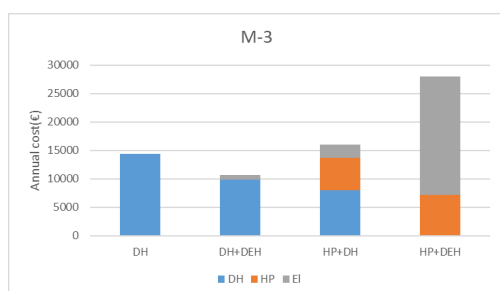
Fig. 5-3 Cost comparison between Old PM and New PM for different alternative solutions.

For the dynamic model based on LCOH, since a much lower heat price can be obtained, the alternatives don't show the same annual cost savings, as shown in Fig 5-4. Using direct electrical heating to cover the peak demand of district heating is still the best alternative; whereas, its saving is much smaller compared to the old and new PMs, which are 19,1%, 19,6% and 25,9% respectively.



(a) M-1

(b) M-2



(c) M-3

Fig. 5-4 Cost comparison amongst M-1, M-2 and M-3 for different alternative solutions.

6 Concluding remarks

District heating (DH) companies are facing several challenges during the upcoming years. A combination of higher operational costs, competition from alternative technologies benefiting from low electricity prices, as well as the need of providing more transparent price information to the end-users puts high pressure on many utilities.

Marginal cost method has been widely used for heat pricing in Sweden as it is a deregulated market. A price model normally includes four components: fixed cost, capacity cost, energy cost and flow cost. Currently some DH companies have updated their district heating prices by increasing the capacity cost in order to encourage consumers to change their behaviors and, therefore, reduce the peak load and consequently the production cost. One problem is that the capacity cost is often based on the historical heat consumption data, and this may not reflect that peak load to be charged accurately in real-time. Meanwhile, the peak load may not happen at the same time for all customers; hence, charging a high capacity cost cannot solve the problem caused by the peak load. A good price model should be able to reflect the dynamic production cost accurately, therefore, motivate consumers to reduce the peak load and save energy at the same time. In addition, the heat price should be predictable and transparent.

A novel dynamic price model has been developed based on the levelized cost of energy, which carefully considers the capital cost, O&M cost and other costs. Since the combined heat and power (CHP) plant produces heat and power simultaneously, the fuel consumption should be allocated for between electricity and heat production, which directly affects the cost for heat production. Three methods have been tested in this work, including allocating fuel according to energy and exergy of products and market method. Results show that the prices based on levelized cost of heat (LCOH) are much lower than those from the real price models, which implies there should be a potential to lower the heat price. The variation of LCOH follows the fluctuation of heat demand and therefore, the price based on LCOH can demonstrate the production cost more accurately. Whereas, its complexity, for example the allocation of fuel cost for the production of electricity and heat in a CHP system, may hinder its practicable application. Meanwhile, the dynamic operation hours of equipment and unpredictable maintenance cost could also introduce large deviations in the calculation of LCOH.

Using artificial neural network for the prediction of heat demand has attracted more and more attention. A model based on Elman neural network (ENN) has been developed to predict the total heat demand in the DH network. Meanwhile, weather conditions, such as ambient temperature, wind speed and direct solar radiance are key input parameters. Their influences on the model accuracy have been studied. Results show that including wind speed can generally result in a lower overall mean absolute percentage error (MAPE) (4.43%) than including direct solar radiance (6.47%); while including direct solar radiance can achieve a lower maximum absolute deviation (71.8%) than including wind speed (81.53%). In addition, even though including both wind speed and direct solar radiance shows the best overall performance (MAPE=6.35%), ENN could not benefit from

the simultaneous introduction of both wind speed and direct solar radiance, according to MAPE.

Price model reforming could lead to a significant change in the expense of customers and affect the selection of energy saving measures. The influences of the dynamic price model based on LCOH are compared with those of the two real price models. Due to the lower heat prices from the dynamic model, the heat expense of consumers would be lower than those charged by using the real price models. Three alternative solutions are assessed in this study: using direct electrical heating (DEH) to provide the peak heating demand combined with DH covering base demand; installing heat pump (HP) to cover base demand combining with DH or DEH to provide peak demand. Results show that due to the low electricity price currently, using DEH to cover the peak demand of district heating and combining DEH and HP can be more economical than DH. Compared with the real price models, the annual cost saving becomes smaller when the proposed dynamic price model is applied, which implies a better competitiveness.

7 References

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A DYNAMIC PRICING MECHANISM FOR DISTRICT HEATING

A novel dynamic price model has been developed based on the levelized cost of heat. This model is expected to promote the competence of district heating and motivate consumers to reduce the peak load and save energy at the same time.

Based on the predicted heat demand, the heat price can be determined, which is able to reflect the production cost accurately. Artificial neural network is a promising method for the prediction of heat demand and ambient temperature, wind speed and direct solar radiance are key input parameters.

Price model reforming could affect the selection of energy saving measures. Due to the low electricity price currently, installing heat pump and using district heating to cover the peak demand would be the most economical alternative.

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