Applied Energy xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Economic valuation of heat pumps and electric boilers in the Danish energy system

Maria Grønnegaard Nielsen [a], Juan Miguel Morales [a,*], Marco Zugno [a], Thomas Engberg Pedersen [b], Henrik Madsen [a]

[a] DTU Compute, Richard Petersens Plads, Bldn. 324, 2800 Kgs. Lyngby, Denmark
[b] COWI, Parallelvej 2, 2800 Kgs. Lyngby, Denmark

HIGHLIGHTS

- We assess the economic value of heat pumps and electric boilers in Denmark.
- The daily operation of a heat and power system is modeled by stochastic programming.
- Deterministic models overestimate the value of heat pumps and electric boilers.
- Heat pumps and electric boilers can reduce the cost of operating the Danish system.
- Falling power prices may boost the future value of heat pumps and electric boilers.

ARTICLE INFO

Article history:
Received 17 April 2015
Received in revised form 5 August 2015
Accepted 26 August 2015
Available online xxxx

Keywords:
Heat market
Electricity market
Heat pump
Electric boiler
Combined heat and power
Stochastic programming

ABSTRACT

Heat pumps (HP) and electric immersion boilers (EB) have great potential to increase flexibility in energy systems. In parallel, decreasing taxes on electricity-based heat production are creating a more favorable economic environment for the deployment of these units in Denmark. In this paper, the economic value of heat pumps and electric boilers is assessed by simulating their day-to-day market performance using a novel operational strategy based on two-stage stochastic programming. This stochastic model is employed to optimize jointly the daily operation of HPs and EBs along with the Combined Heat and Power (CHP) units in the system. Uncertainty in the heat demand and power price is modeled via scenarios representing different plausible paths for their future evolution. A series of case-studies are performed using real-world data for the heat and power systems in the Copenhagen area during four representative weeks of 2013. We show that the use of stochastic operational models is critical, as standard deterministic models provide an overestimation of the added benefits from the installation of HPs and EBs, thus leading to over-investment in capacity. Furthermore, we perform sensitivity studies to investigate the effect on market performance of varying capacity and efficiency for these units, as well as of different levels of prices in the electricity market. We find that these parameters substantially affect the profitability of heat pumps and electric boilers, hence, they must be carefully assessed by potential investors.

1. Introduction

Denmark has committed to pursue a 100%-renewable energy supply by 2050 [1]. Furthermore, half of the electricity consumption is to be provided by wind power by 2020. In view of these ambitious targets, integration across different energy systems is seen as fundamental, as it can improve the exploitation of the flexibility of heat and transport systems to support the growth of intermittent renewable power sources [2,3]. Non-renewable fuels, such as oil and coal, are currently used to produce a significant share of the Danish heat and power [4]. Traditionally, these have been widely used for generating heat and power through the use of highly efficient Combined Heat and Power (CHP) plants. However, the reconciliation of the large-scale integration of wind power production along with the wide use of CHP units for heat and power production (cogeneration) will be a challenge for future energy systems. Indeed, the profitability of cogeneration can be dramatically reduced in periods of large wind power production as wholesale power prices drop [5].

* Corresponding author. Tel.: +45 4525 3428.
E-mail addresses: jmmgo@dtu.dk (J.M. Morales), mazu@dtu.dk (M. Zugno), tep@cowi.dk (T.E. Pedersen), hmad@dtu.dk (H. Madsen).

http://dx.doi.org/10.1016/j.apenergy.2015.08.115
0306-2619/

A partial solution to this problem consists in an efficient joint management of the available heat and power units that takes into account the future evolution of heat demand and power prices. These are in turn driven by renewable power output, among other factors [2]. Furthermore, heat pumps (HP) and electric immersion boilers (EB) can be installed to increase the flexibility of the system (see, e.g., [6], where equipping CHP plants with heat pumps is suggested with a view to effectively increasing the penetration of wind power in the Danish power system).

Both HPs and EBs use electricity to generate heat. In general, units of this type may enhance the power system flexibility as electricity is used as fuel. Indeed, with an increasing share of fluctuating renewable power production in the power system, the number of events in which renewable power generation cannot be reliably accommodated in the grid or even exceeds the demand grows. During these events, the market price for electricity becomes close to zero, zero or even negative. Therefore, during these events, it may be beneficial, both from the standpoint of a single company and for the system as a whole, to utilize electricity to produce heat by means of HPs and/or EBs. From a purely thermodynamic point of view, transforming electrical energy into heat in an EB is considerable less efficient than doing it through a HP.[1] In contrast, EBs have lower investment costs and fast-regulation capabilities (with no start-up cost or ramping constraints), which makes them very suitable for the provision of grid ancillary services. All together, the conversion of electricity into heat via EBs and HPs may become economically attractive in energy systems with a high penetration of fluctuating renewable energy sources. A more thorough introduction to heat pumps and electric boilers can be found in [7,8].

The deployment of HPs and EBs in the Danish district heating systems began during the last decade. However, the extent of this trend has been rather limited as high taxation has constrained the profitability of these units. In 2013 a significant tax reduction was decided for this specific type of production technology, favoring especially the HP [9]. Even though the deployment of HPs and EBs is a relatively new phenomenon, previous research on the optimization and economic assessment of combined heat and power production systems including these units is abundant, some dating back several decades (see, e.g., [10] and references therein). However, to the best of our knowledge, all these studies were conducted under a deterministic framework.

The increasing focus on cogeneration, together with a greater awareness of the uncertainty in electricity prices and heat demand, has resulted in numerous papers jointly dealing with these aspects in the last decades. Deterministic optimization models to maximize the profit of heat and power production systems are proposed in [11,12] and are also available in software packages such as energyPRO [13]. The stochastic programming approach [14] to the same problem is followed in [15,16]. Finally, a model based on robust optimization is proposed in [17]. Furthermore, Zapata et al. [18] developed a deterministic optimization scheme to assess the potential of coordinated real-time market operation of micro-CHP and PV units. None of these works, however, include HPs and EBs. Furthermore, the focus in this paper is on assessing the value created by these heat production units rather than evaluating operational strategies.

Existing literature on economic valuation and investment analysis in heat and power systems has relied on deterministic operational models so far. For example, the deterministic analysis tool, Balmorel, models the entire Greater Copenhagen district heating system, including the Nordic power market, and provides long-term information on an aggregated level [19]. The profitability of different CHP technologies in a smart energy system is assessed in [20] using the deterministic model Energyplan. Furthermore, Blarke and Dotzauer [21] assess the economic value of a HP utilizing flue gas from a CHP. Hendriksen [22] analyzes the economic potential for a HP to utilize waste heat from industrial facilities, but not in the context of combined heat and power production. In [23], a stochastic programming model is used to evaluate the value of HPs and EBs in a system including wind power. In contrast to the work in this paper, only wind power is considered stochastic. Furthermore, the analysis is only carried out for a short period in February, where wind power production usually fluctuates much and thus a high benefit is to be expected from introducing HPs and EBs.

Although the use of stochastic programming in the operation of systems of power production facilities is well established, see [24,25] and references therein, the economic assessment of the value of HPs and EBs using daily operational models for heat and power systems based on this state-of-the-art stochastic approach remains not studied. Therefore, the contributions of this paper are threefold. Firstly, we propose a stochastic programming model for the joint daily operation of heat and power systems that exploits probabilistic forecasts of heat demand and power prices. This model represents the decision-making process that utilities conduct in an uncertain market environment. Secondly, we use this model to assess the yearly return of potential investments in heat pumps and electrical boilers in an already existing energy system. These two contributions together lead to a methodological and modeling framework for the economic valuation of heat and power systems that can be easily tailored to the specific market and system conditions prevailing in the area, region or country of interest. In this line, our third and last contribution is the use of such a modeling framework to analyze a series of case studies based on real-world data for the Copenhagen area under the current conditions of the Danish heat and power markets and systems. We assess the sensitivity of our results to different technological and market parameters such as unit efficiencies and market-price level.

This paper has the following structure. The physical and market setups that serve as the basis for our model are presented in Sections 2 and 3, followed by the mathematical model in Section 4. The methods for forecasting the heat load and the power price are introduced in Section 5. Results from the proposed model and the conducted analyses are discussed in Section 6. Finally, conclusions are duly drawn in Section 7.

2. Physical setup

Fig. 1 shows a simple overview of the physical system considered in this paper. Two different CHP units are included, one coal-fired extraction unit (denoted in the remainder of this paper as “ex CHP”) and one biomass-fueled back-pressure unit (“bp CHP”). The extraction unit produces at a variable heat-to-power ratio with a variable efficiency, which is lowest when only power is produced. The back-pressure CHP plant produces at a constant heat-to-power ratio. More details on the operation of these plants can be found in [7]. Both units feed heat directly to the transmission network and to a large heat accumulator. The transmission network supplies several local distribution networks, only two of which are shown in the illustration. The HP is connected to a local distribution network and a small local heat accumulator. The HP operates as a negative load for the system, i.e., it is assumed that the size and heat demand of the distribution network is large enough for the HP to produce at any time. Both the HP and EB consume electricity and produce heat. Red dashed lines represent heat transfer, while black arrows represent electricity inputs or outputs.

[1] A HP utilizes energy from a low-temperature heat source such as waste water, sea or air in the process of producing heat. This gives a HP a higher coefficient of performance (COP), which is the power-to-heat ratio, compared to an EB.

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

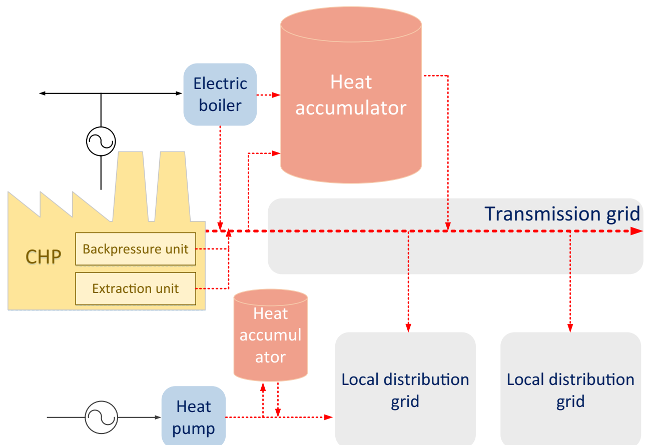

Fig. 1. District heating system comprising two CHP units, an EB, a HP and a large and a local heat accumulator.

This system, without the HP and EB, is a simplification of Amagerværket, a CHP plant supplying the Greater Copenhagen area [26].

The heat supply into the transmission network must be performed at a temperature of around 100 °C. Currently, HPs are only designed to produce heat with a supply temperature of up to 85 °C [7]. This means that the location of the HP is presently limited to the distribution network, which directly serves end users and thus has lower temperature requirements. The EB does not have such a temperature restriction. Therefore, it can be located at the most beneficial site. The taxation scheme on the usage of these units is the main driver influencing their location.

2.1. Taxes and fees for electricity-driven heat production

The operational cost for heat pumps and electric boilers depends on the variable electricity prices. In addition, a number of taxes and fees applies.

Producers using HPs and EBs can, under specific circumstances, choose between paying taxes either for their electricity consumption or for their heat production [27]. Generally, the electricity tax is more favorable to units with a high power-to-heat ratio, such as heat pumps, whereas the heat tax is preferred for units with lower ratios, e.g., electric boilers. According to [28], the HP and EB production is not taxed if the units are directly connected to and supplied by a sustainable energy such as a biomass fueled CHP unit. As taxes may account for more than 50% of the production cost for an EB, this largely justifies placing the EB at the CHP plant.

The Danish tax system for heat and power production and consumption is complex and is subject to constant changes and amendments. Further details can be found in [7,27].

3. Market setup

The electricity to be used by the HP should either be produced internally by a power unit or bought in the electricity market. For the EB the electricity must be supplied by the biomass backpressure CHP unit to be exempted from the energy tax. The heat produced by both the HP and EB is to be sold in the heat market. Therefore, both the (day-ahead) electricity and heat markets are relevant for the operation of these units.

3.1. Day-ahead electricity market

The Nordic electricity market, Nord Pool, constitutes the natural trading floor for the electricity produced by the CHP plant or consumed by the heat pump or the electric boiler. The day-ahead market, Elspot, is the most widely used, as it accounts for 71% of the total volume of traded electricity [29].

The gate closure of the Elspot market is set at noon, when all the participants must have submitted their offers and bids for power delivery and consumption at every hour of the following day. Through their offers (bids), market participants specify supply (demand) curves, which indicate the price required (offered) for a certain level of production (consumption). The dispatch for each individual participant and the prices are determined by the market operator, which runs a market clearing process aimed at maximizing social welfare [30]. In the event of low prices, the HP and EB benefit from buying electricity and producing heat. On the contrary, high prices favor CHP plants, as these units produce electricity along with heat.

For simplicity, in this paper we make the assumption that the considered utility trades power exclusively on the day-ahead market. Extensions of this work with the inclusion of other markets, e.g., bilateral, balancing or reserve, is left as future work (see, for instance [31], where the authors discuss the benefits of having CHP plants contributing to the provision of ancillary services for the electrical grid).

3.2. Heat market

The daily heat dispatch in Copenhagen is run by Varmelast.dk [32], which is owned by the three major heat distributors/transmitters. The process is outlined in Fig. 2. Furthermore, the price for heat in the Danish heat market is agreed, and thus fixed and known, in advance between suppliers of district heating and distributors/transmitters through mid-term contracts.

The most relevant stages for this paper are the last two. Based on a pre-determined heat dispatch, the utility has to plan both the heat and power production before the day-ahead power price is disclosed. Since neither the actual heat demand nor the power price are known, decisions at this stage are based on forecasts and must allow for some flexibility so that the system can adapt to all possible contingencies.

As the power production plan is to be determined along with the heat schedule before noon, utilities are not flexible when specifying the power supply offer at the day-ahead market, i.e., their offer is inelastic. This implies that they may have to face an unfavorable electricity price, possibly resulting in financial losses, to guarantee a sufficient delivery of heat to the transmission network.

The management of a portfolio of different units is not trivial and calls for the use of optimization techniques. The HP and EB can only consume power, but CHP plants can produce power and heat in different ratios and with different efficiencies. Furthermore, in view of the uncertainty in heat demand and power prices, the use of stochastic optimization techniques, such as stochastic programming, is highly appropriate to operate this type of systems.

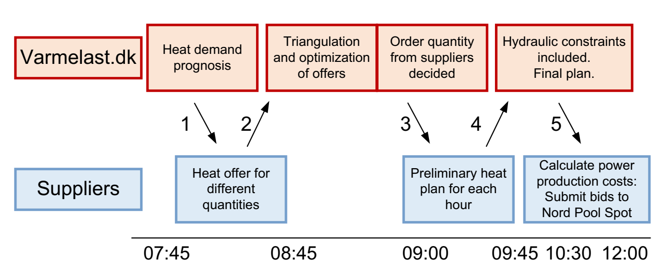

Fig. 2. Timeline for Varmelast.dk heat dispatch process with inspiration from [32].

4. Model

This section presents a deterministic and a stochastic programming model to optimize the operation of the CHP system sketched in Fig. 1. The notation we use is indicated in Tables 1 and 2.

4.1. Deterministic model

The objective is to minimize total operating costs, $c_t^{det,tot}$, i.e.,

$$\min. \sum_t c_t^{det,tot} \tag{1}$$

where $c_t^{det,tot}$ is given by:

$$\begin{aligned} c_t^{det,tot} &= \hat{p}_t^{spot}\left(p_t^{con} - p_t^{prod}\right) - \left(p_t^{bp} - \left(q_t^{d,EB} + q_t^{s,EB}\right)\right)c^{bio} \\ &\quad + \pi_t^{tax,HP} + \pi_t^{tax,EB} + \pi_t^{tax,bp} + \pi_t^{tax,ex} + c^{f,bp}f_t^{bp} + c^{f,ex}f_t^{ex} \\ &\quad + c^{su}\left(i_t^{su,bp} + i_t^{su,ex}\right) + c^{sd}\left(i_t^{sd,bp} + i_t^{sd,ex}\right) \\ &\quad + c^{su,HP}i_t^{su,HP} + c^{inf}q_t^{inf} \end{aligned} \tag{2}$$

The first term in (2) represents the cost of the power consumed by the EB and HP minus the expected turnover from the power traded on the Elspot market. It is followed by a term representing the subsidy for power produced from biomass and not used by the EB. The following four terms are the tax costs for the HP, EB, bp CHP and ex CHP, respectively, which are calculated as follows

$$\pi_t^{tax,HP} = \frac{1}{COP^{HP}}\left(q_t^{d,HP} + q_t^{s,HP}\right)\left(c^{tax,el} + c^{tariff,net}\right), \quad \forall t \tag{3}$$

$$\pi_t^{tax,EB} = \left(q_t^{d,EB} + q_t^{s,EB}\right)c^{tariff,net}, \quad \forall t \tag{4}$$

$$\pi_t^{tax,bp} = \frac{1}{r^{tax,f}}\left(q_t^{d,bp} + q_t^{s,bp}\right)c^{NO_x}, \quad \forall t \tag{5}$$

$$\pi_t^{tax,ex} = \frac{1}{r^{tax,f}}\left(q_t^{d,ex} + q_t^{s,ex}\right)\left(c^{tax,coal} + c^{CO_2} + c^{NO_x}\right), \quad \forall t \tag{6}$$

The second line of (2) also includes the fuel costs for the two CHP units. Finally, the last four terms of the objective function correspond to the start-up costs incurred by the two CHP units and the HP, shut-down costs for the CHPs, and the cost of the heat demand not served.

Objective function (2) is given by running costs, except for the term equal to minus the power sale revenue. Since the price for heat is fixed in advance, and c^{inf} is made sufficiently high to ensure that the heat load is met whenever feasible, objective function (2) can also be interpreted as minus the profit made by the owner of the CHP system depicted in Fig. 1.

4.1.1. Heat balance

Eq. (7) enforces the heat balance. Variable q_t^{inf} is introduced to allow for a feasible solution in case that the heat demand, d_t, cannot be met. The use of this variable is penalized in the objective function.

$$q_t^{d,bp} + q_t^{d,HP} + q_t^{d,EB} + q_t^{d,s} + q_t^{d,s1} + q_t^{d,ex} = d_t - q_t^{inf}, \quad \forall t \tag{7}$$

Table 1
Sets and decisions variables for the stochastic and the deterministic model.

Indices	
t	Time index for hourly period
ξ	Scenario index for stochastic model
k	CHP unit index (bp CHP, ex CHP)
Decision variables	
p_t^{prod}	$\in \mathbb{R}^+$ Total electricity production at time t
p_t^{con}	$\in \mathbb{R}^+$ Total electricity consumption at time t
$q_t^{s,bp}$	$\in \mathbb{R}^+$ Heat production from bp CHP to storage, s
$q_t^{d,bp}$	$\in \mathbb{R}^+$ Heat production from bp CHP to demand at time t
$q_t^{s,ex}$	$\in \mathbb{R}^+$ Heat production to storage s from ex CHP
$q_t^{d,ex}$	$\in \mathbb{R}^+$ Heat production to demand from ex CHP
$q_t^{s1,HP}$	$\in \mathbb{R}^+$ Heat production from HP to storage $s1$ at time t
$q_t^{d,HP}$	$\in \mathbb{R}^+$ Heat production from HP to demand at time t
$q_t^{s,EB}$	$\in \mathbb{R}^+$ Heat production from EB to storage s at time t
$q_t^{d,EB}$	$\in \mathbb{R}^+$ Heat production from EB to demand at time t
$q_t^{d,s}$	$\in \mathbb{R}^+$ Amount taken from storage s at time t
$q_t^{d,s1}$	$\in \mathbb{R}^+$ Amount taken from HP storage $s1$ at time t
q_t^{inf}	$\in \mathbb{R}^+$ Heat demand not covered at time t
s_t^s	$\in \mathbb{R}^+$ Amount in storage s at time t
s_t^{s1}	$\in \mathbb{R}^+$ Amount in HP storage $s1$ at time t
$p_t^{f,ex}$	$\in \mathbb{R}^+$ Max power for constant fuel for ex CHP
f_t^{ex}	$\in \mathbb{R}^+$ Fuel consumption from ex at time t
f_t^{bp}	$\in \mathbb{R}^+$ Fuel consumption from bp CHP at time t
p_t^{ex}	$\in \mathbb{R}^+$ Power production from ex CHP at time t
i_t^{bp}	$\in \mathbb{B}$ Is one if bp CHP is producing at time t
$i_t^{su,bp}$	$\in \mathbb{B}$ Is one if bp CHP is in start-up at time t
$i_t^{sd,bp}$	$\in \mathbb{B}$ Is one if bp CHP is in shut-down at time t
i_t^{ex}	$\in \mathbb{B}$ Is one if ex CHP is producing at time t
$i_t^{su,ex}$	$\in \mathbb{B}$ Is one if ex CHP is in start-up at time t
$i_t^{sd,ex}$	$\in \mathbb{B}$ Is one if ex CHP is in shut-down at time t
i_t^{HP}	$\in \mathbb{B}$ Is one if HP is producing at time t
$i_t^{su,HP}$	$\in \mathbb{B}$ Is one if HP is in start-up at time t

Table 2
Parameters for the stochastic and the deterministic model.

Parameters	
$\hat{p}_t^{spot}$	Forecast spot price at time t
$\hat{d}_t$	Forecast heat load at time t
C^s	Storage capacity
C^{s1}	HP storage capacity
C^{HP}	Heat production capacity for HP
C^{EB}	Heat production capacity for EB
C^{bp}	Heat production capacity for bp CHP
C^{ex}	Heat production capacity for ex CHP
$c^{f,bp}$	Fuel cost for bp CHP (biomass)
$c^{f,ex}$	Fuel cost for ex CHP (coal)
COP^{HP}	COP for HP
η^{bp}	Total efficiency for bp CHP
η^{ex}	Power efficiency for ex CHP
R^{bp}	Max ramp up and down rate for bp CHP
R^{ex}	Max ramp up and down rate for ex CHP
S^{flow}	Maximum flow to and from storage
S^{loss}	Loss when using heat from storage
$c\upsilon^{ex}$	Power to heat ratio for ex CHP in extraction operation
cb^{bp}	Power to heat relationship for bp CHP
cb^{ex}	Power to heat ratio for extraction CHP in back-pressure operation
$P^{min,bp}$	Minimum power production from bp CHP
$P^{max,ex}$	Maximum power production from ex CHP
$P^{min,ex}$	Minimum power production from ex CHP
$Q^{min,HP}$	Minimum heat production from HP
c^{su}	Start up cost for CHP units
c^{sd}	Shut-down cost for CHP units
$c^{su,HP}$	Start up cost for HP
$c^{tax,coal}$	Tax for production from coal
$c^{tariff,net}$	Distribution fee for electricity consumption
$c^{tax,el}$	Electricity consumption tax
c^{CO_2}	CO_2 tax for heat production from fossil fuels
c^{NO_x}	NO_x tax for heat production from fossil fuels
c^{bio}	Subsidy for power produced by biomass bp CHP
c^{inf}	Penalty for the heat demand not being satisfied
$r^{tax,f}$	Ratio between heat production and fuel to be taxed
$c^{tax,heat}$	Tax on heat production Elpatronlov [33] (E.A.4.2.9)

4.1.2. Total power production and consumption

The planned production of electricity, p_t^{prod}, is defined as the sum of the power outputs of the two CHP units, that is,

$$p_t^{prod} = p_t^{bp} + p_t^{ex}, \quad \forall t \tag{8}$$

The power consumed by the EB and HP, p_t^{con}, is determined as

$$p_t^{con} = q_t^{s,EB} + q_t^{d,EB} + \frac{1}{COP^{HP}}\left(q_t^{d,HP} + q_t^{s,HP}\right), \quad \forall t \tag{9}$$

4.1.3. Tax- and subsidy-related constraints

In order for the EB to be exempt from the electricity consumption tax, its power consumption must always come from the biomass back-pressure CHP. Thus, it is required that

$$q_t^{s,EB} + q_t^{d,EB} \leqslant p_t^{bp}, \quad \forall t \tag{10}$$

Note that no subsidy is paid for the part of the back-pressure electricity production that is used for the EB, as it is not delivered to the grid.

4.1.4. Power production and fuel consumption of CHP units

The power production and fuel usage from the back-pressure CHP is calculated in (11) and (12) using the power efficiency η^{bp}:

$$p_t^{bp} = \left(q_t^{s,bp} + q_t^{d,bp}\right) cb^{bp}, \quad \forall t \tag{11}$$

$$f_t^{bp} = \frac{1}{\eta^{bp}}\left(p_t^{bp} + q_t^{s,bp} + q_t^{d,bp}\right), \quad \forall t \tag{12}$$

Due to the operational possibilities of an extraction CHP, explained in [7], heat and power outputs are not bound to follow a proportional relationship. The power production is, instead, constrained to be within a feasible region that depends on the heat production:

$$p_t^{ex} \leqslant c\upsilon^{ex}\left(q_t^{d,ex} + q_t^{s,ex}\right) + P^{max,ex}, \quad \forall t \tag{13}$$

$$p_t^{ex} \geqslant cb^{ex}\left(q_t^{d,ex} + q_t^{s,ex}\right) + P^{min,ex}, \quad \forall t \tag{14}$$

Constraints (15) and (16) link power and heat production to the corresponding fuel consumption f_t^{ex}:

$$p_t^{ex} = c\upsilon^{ex}\left(q_t^{d,ex} + q_t^{s,ex}\right) + p_t^{f,ex}, \quad \forall t \tag{15}$$

$$f_t^{ex} = \frac{1}{\eta^{ex}} p_t^{f,ex}, \quad \forall t \tag{16}$$

4.1.5. Ramping

The ramping constraints of the CHP units are formulated as

$$\left(q_t^{d,k} + q_t^{s,k}\right) - \left(q_{t-1}^{d,k} + q_{t-1}^{s,k}\right) \leqslant R^k, \quad \forall t, k \tag{17}$$

$$\left(q_t^{d,k} + q_t^{s,k}\right) - \left(q_{t-1}^{d,k} + q_{t-1}^{s,k}\right) \geqslant -R^k, \quad \forall t, k \tag{18}$$

These constraints imply that the CHP units can only increase or decrease their production by a limited amount, R^k, from one hour to the next. Since the capacity of the HP is not very large relative to the CHP units, we disregard the ramping limits of the HP. The EB can go from zero to full load, and vice versa, in a matter of minutes or seconds. Thus, ramping constraints are not relevant for this unit.

4.1.6. Start-up and shut-down

Start-up and shut-down costs are non-zero for both the back-pressure and the extraction CHP units. The HP also incurs start-up and shut-down costs. However, shut-down costs for the HP are comparatively much smaller than start-up costs. Hence, they are omitted here for simplicity. In (19)–(21), binary variables i_t^{bp}, i_t^{ex} and i_t^{HP} are one if the heat or power production of the respective unit is different from zero:

$$q_t^{s,bp} + q_t^{d,bp} \leqslant i_t^{bp} C^{bp}, \quad \forall t \tag{19}$$

$$p_t^{ex} + q_t^{s,ex} + q_t^{d,ex} \leqslant i_t^{ex}\left(P^{max,ex} + C^{ex}\right), \quad \forall t \tag{20}$$

$$q_t^{s,HP} + q_t^{d,HP} \leqslant i_t^{HP} C^{HP}, \quad \forall t \tag{21}$$

Note that constraint (20) includes the power production, p_t^{ex}, because unlike the back-pressure CHP unit, the extraction plant can produce power without simultaneously producing heat.

Eqs. (22) and (23) are logical constraints on the binary start-up variables, $i_t^{su,bp}$, $i_t^{su,ex}$ and $i_t^{su,HP}$:

$$i_t^{su,k} \geqslant i_t^k - i_{t-1}^k, \quad \forall t, k \tag{22}$$

$$i_t^{su,HP} \geqslant i_t^{HP} - i_{t-1}^{HP}, \quad \forall t \tag{23}$$

Constraints modeling the shut-down of CHP units are formulated as follows:

$$i_t^{sd,k} \geqslant i_{t-1}^k - i_t^k, \quad \forall t, k \tag{24}$$

4.1.7. Minimum load constraints

A minimum power and heat production is required when the CHP units and the heat pump are running, respectively. This is enforced by the following constraints:

$$p_t^k \geqslant i_t^k P^{min,k}, \quad \forall t, k \tag{25}$$

$$q_t^{s,HP} + q_t^{d,HP} \geqslant i_t^{HP} Q^{min,HP}, \quad \forall t \tag{26}$$

4.1.8. Storage operation

The two storages in Fig. 1 are characterized by their state transition Eqs. (27) and (28), which describe their heat level at any point in time. These equations are formulated as the previous heat level plus the net heat flow to the storage at time t. The net heat flow to the storage is given by the amount of heat transferred from the production units (CHP plants and EB or HP) to the storage minus the amount of heat that is extracted from the storage to supply the demand:

$$s_t^s = s_{t-1}^s + q_t^{s,bp} + q_t^{s,ex} + q_t^{s,EB} - s^{loss} q_t^{d,s}, \quad \forall t \tag{27}$$

$$s_t^{s1} = s_{t-1}^{s1} + q_t^{s,HP} - s^{loss} q_t^{d,s1}, \quad \forall t \tag{28}$$

In the previous equations, s^{loss} is introduced to model a heat loss when using the storage.

There is a physical limit on the amount of heat that can flow to and from the storage. This constraint is modeled as follows:

$$q_t^{d,s} \leqslant S^{flow}, \quad \forall t \tag{29}$$

$$q_t^{s,bp} + q_t^{s,EB} + q_t^{s,ex} \leqslant S^{flow}, \quad \forall t \tag{30}$$

We assume that the smaller local storage can be emptied or refilled completely in one hour. Hence, no lower or upper bounds for the heat flow into or from this storage are needed.

4.1.9. Capacity constraints

The following capacity constraints are required to limit the production from the EB and the heat content in the storages.

$$s_t^s \leqslant C^s, \quad \forall t \tag{31}$$

$$s_t^{s1} \leqslant C^{s1}, \quad \forall t \tag{32}$$

$$q_t^{s,EB} + q_t^{d,EB} \leqslant C^{EB}, \quad \forall t \tag{33}$$

Note that the capacity limits of the CHP units and the HP are enforced by (19)–(21), respectively.

The objective function (2) and constraints (3)–(33) constitute the deterministic model to optimize the daily operation of the CHP system.

4.2. Stochastic model

Both the electricity price and the heat demand are uncertain. In the deterministic model presented above, day-ahead scheduling and trading decisions are made on the basis of a point forecast for the stochastic parameters, i.e., a single value typically representing the expected realization of the uncertainty.

In practice, when uncertain parameters like the heat demand are disclosed in real-time, utilities have the possibility of re-adjusting their schedule so that the actual production matches the realized consumption. However, when making decisions in advance, deterministic models neglect the possibility of making real-time adjustments. In other words, such models do not consider the cost of re-adjustment. In the technical literature, decisions that are to be made in advance are referred to as "here-and-now", while decisions that can be adapted to the outcome of the uncertainty are referred to as "recourse".

Stochastic optimization differs from its deterministic counterpart in that it explicitly models the recourse stage in the decision-making process. When determining the optimal here-and-now solution, stochastic optimization models consider both the scheduling cost and a probabilistic measure (such as the expected value or a risk metric) of the readjustment costs. This way, stochastic optimization can make better decisions by providing higher flexibility to cope with contingencies in real-time.

A particular method for stochastic optimization is stochastic programming. In a stochastic programming model, a finite number of samples of the uncertain parameters is considered. An individual instance of the recourse variables is then assigned to each of these scenarios. As a result of the discretization process, a finite number of here-and-now and recourse variables are to be optimized, resulting in a tractable optimization problem. We refer the reader to [14] for further details on this technique.

This approach is the subject of the following section. The notation employed is as described in Tables 1 and 2. However, the uncertain parameters and the recourse variables are now denoted by the additional index ξ, linking the relevant parameter or variable to a particular realization of the uncertainty (scenario). For example, parameters $d_{t,\xi}$ and $p^{spot}_{t,\xi}$ represent the realized heat demand and electricity price for scenario ξ and time t, respectively. Similarly, $i^{su,HP}_{t,\xi}$ is the readjustment of the HP start-up decision for time t and scenario ξ. Furthermore, the symbol Δ is employed to denote a change or adjustment between the day-ahead plan and the actual real-time value of a variable. For example, $\Delta p^{prod}_{t,\xi}$ represents the change in electricity production for scenario ξ.

4.2.1. Objective function

In the stochastic programming model, we formulate the objective function (34) as the sum of the first stage cost, $c^{det,tot}$, as defined in (2), and the expected value of the recourse cost, $E[Q(x,\xi)]$, that is,

$$\min.\ \sum_t c^{det,tot}_t + E[Q(x,\xi)] \tag{34}$$

where

$$\begin{aligned} Q(x,\xi) = \min.\ \sum_t \Big(& \Delta\pi^{HP,tax}_{t,\xi} + \Delta\pi^{EB,tax}_{t,\xi} + \Delta\pi^{ex,tax}_{t,\xi} + \Delta\pi^{bp,tax}_{t,\xi} \\ & - \left(\Delta p^{bp}_{t,\xi} - \left(\Delta q^{d,EB}_{t,\xi} + \Delta q^{d,EB}_{t,\xi}\right)\right) c^{bio,sup} + c^{f,bp}\Delta f^{bp}_{t,\xi} + c^{f,ex}\Delta f^{ex}_{t,\xi} \\ & + c^{inf}\Delta q^{inf}_{t,\xi} + c^{su}\left(\Delta i^{su,bp}_{t,\xi} + \Delta i^{su,ex}_{t,\xi}\right) + c^{su,HP}\Delta i^{su,HP}_{t,\xi} \\ & + c^{sd}\left(\Delta i^{sd,bp}_{t,\xi} + \Delta i^{sd,ex}_{t,\xi}\right)\Big) \end{aligned} \tag{35}$$

The first four terms represent the change in tax costs followed by the change in the subsidy for biomass-produced power. Then, the cost associated with the change in fuel consumption and the cost of uncovered heat demand are stated. Finally, the last three terms account for the adjustments costs related to start-ups and shut-downs.

The CHP system must remain in power balance, that is,

$$\Delta p^{prod}_{t,\xi} - \Delta p^{con}_{t,\xi} = 0, \quad \forall t,\xi \tag{36}$$

where we have assumed that the CHP system does not exchange electricity in the real-time market (i.e., it self-balances the power deviations from the day-ahead power production schedule).

To further clarify this constraint, let us consider a scenario where the heat demand is higher than expected. In such a case, a CHP unit may be required to produce additional heat, and thus also power. This implies that the EB or HP should increase their power consumption accordingly. If this is not considered, as in the deterministic model, it can result in the heat demand not being satisfied. In the stochastic setup, the first-stage decisions are made so that second-stage decisions can adapt efficiently to the realizations of the stochastic heat demand.

Constraints (3)–(33) are also imposed in the stochastic model to ensure that the resulting day-ahead unit commitment and dispatch solutions are feasible. Besides, the same constraints have to be replicated for each scenario in order to enforce that the actual real-time dispatch of the units, resulting from the combination of pre-dispatch and readjustment, is feasible. As an example, let us consider the heat balance constraint, which for the day-ahead dispatch is enforced by (7). The corresponding constraints imposing heat balance in real-time are the following:

$$\begin{aligned} & q^{d,bp}_t + q^{d,HP}_t + q^{d,EB}_t + q^{d,s}_t + q^{d,s1}_t + q^{d,ex}_t + \Delta q^{d,bp}_{t,\xi} + \Delta q^{d,HP}_{t,\xi} \\ & + \Delta q^{d,EB}_{t,\xi} + \Delta q^{d,s}_{t,\xi} + \Delta q^{d,s1}_{t,\xi} + \Delta q^{d,ex}_{t,\xi} \\ & = d_{t,\xi} - q^{inf}_t - \Delta q^{inf}_{t,\xi}, \quad \forall t,\xi \end{aligned} \tag{37}$$

This type of constraints exists for all the features presented in (11)–(33) in the deterministic model. Furthermore, the non-negativity definitions in Table 1 should also be true after introducing the recourse variables.

5. Forecasts and scenario generation

This section describes the method employed for probabilistic forecasting of the heat load and spot price used as input to the deterministic and the stochastic optimization models. We construct time series models to describe the heat load and spot price and provide forecasts of the heat load and spot price up to 38 h ahead.

Forecasting the spot price is generally considered highly complex and is a research topic of its own [34,35]. However, as we focus on the economic analysis, the proposed forecasting models only feature the main principles needed to construct the necessary input data, without aiming at improving the state-of-the-art.

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

5.1. Forecasting heat load and spot price

The data available for the heat load consist of the expected hourly heat demand in the Greater Copenhagen area for the full year of 2013.

Monthly deviations are between 5% and 15% [32], being highest in the spring and fall where the weather is less predictable. A clear seasonal trend is present in the heat demand data, due to the strong difference in temperature between summer and winter. Furthermore, a daily seasonality is observed due to specific consumption patterns during the day.

Since the realized heat load was not available, we fit a time-series model to the available heat prognosis. The following AR model [36] proved to be appropriate to model the data at hand:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-24} + \phi_4 Y_{t-25} + \epsilon_t \tag{38}$$

where Y_t is the heat demand at time t, ϵ_t is a white noise process $\sim N(0, \sigma)$ and ϕ_1–ϕ_4 are parameters estimated using the prediction error method [36]:

$$(\phi_1, \phi_2, \phi_3, \phi_4) = (1.35, -0.40, 0.42, -0.37) \tag{39}$$

The standard deviation of the innovation process is:

$$\sigma = 26.66 \text{ MWh} \tag{40}$$

Forecasts up to 38 h ahead are issued, resembling reality where day-ahead forecasts are provided to utilities at 10 am to support their offering process.

The data available for the expected heat demand is based on a heat market with two suppliers. As this paper adopts the viewpoint of one supplier, the demand is scaled accordingly.

Regarding the electricity spot price, hourly historical data are publicly available at [37]. Similar to the heat load, but less significantly, the spot price shows a daily pattern with the price being lowest at night. Correlation between the spot price and heat demand is non-negligible and thus a regression model with the heat demand forecast as explanatory variable is suggested to model the spot price, see [30] for further explanation.

A seasonal second order autoregressive model is identified as suitable [36]. The spot price at time t, X_t, is described by:

$$X_t = \theta_1 X_{t-1} + \theta_2 X_{t-2} + \theta_3 X_{t-24} + \theta_4 Y_t + \epsilon_t \tag{41}$$

where the explanatory variable Y_t is the heat demand forecast at time t. The parameter values are estimated to:

$$(\theta_1, \theta_2, \theta_3, \theta_4) = (1.10, -0.26, 0.15, 0.002) \tag{42}$$

and the standard deviation of the innovation process is found to be:

$$\sigma = 34.2 \text{ MWh}$$

Including wind speed forecasts as explanatory variables would improve the forecasts, since wind power production is found to have a strong negative correlation with the spot prices [34]. We leave this as a direction for future improvement of the model.

To provide the necessary input to the stochastic-programming model, we generate 100 scenarios, each corresponding to a possible realization of the stochastic process [30].

6. Model results

In this section, we present results obtained from the comparison between the stochastic and the deterministic models on a setup that is based on the actual heat system Amagerværket, which serves part of the Greater Copenhagen area. We consider the first week of February, May, August and November to represent the yearly variation in heat demand and electricity spot price. To set the initial content of the heat storages and the initial on/off states and production levels of the CHP plant, the heat pump and the electric boiler in each of the analyzed weeks, the operation of the CHP system is simulated over an extra day prior to the week in question. The content of the heat tanks associated with the CHP plant and the heat pump for the first hour of this extra day are fixed at 200 MWh and 0 MWh, respectively, with the only purpose of guaranteeing a feasible starting solution. On the other hand, we let the heat storages to be fully emptied by the end of each week. The consideration of any other final value for the heat content of the storages should not affect, at least significantly, the relative difference in costs of the stochastic and the deterministic operational models, insofar as both models are run under the same conditions. These two models are Mixed Integer Linear Programs (MILP), with the stochastic model being of larger size due to the use of scenarios. We employed CPLEX, see [38], within the modeling environment GAMS running on a computer with an Intel Core i5 processor at a clock-speed of 1.7 GHz and 4 GB of RAM memory.

The parameter values used for both the deterministic and the stochastic models are displayed in Table 3. The optimization considers a 24-h time horizon, i.e., each day is optimized separately. However, the production and storage levels at the last hour of each day are used as a fixed input to the following day.

Solving the deterministic model for the full year of 2013 reveals that the back-pressure CHP is generally used throughout the whole year and is basically the only unit operating during summer. The extraction CHP is mainly used during winter, early spring and late autumn. Both observations are consistent with the production patterns of the two existing CHP units at Amagerværket, see [26]. The HP appears in the production schedule, mainly during winter, spring and autumn where more frequent low electricity-price events occur. On the basis of this preliminary analysis, we conclude

Table 3
Parameter values.

Parameter	Value	Unit
C^{s}	750	MWh
C^{s1}	200	MWh
C^{HP}	75	MW
C^{EB}	75	MW
C^{bp}	250	MW
C^{ex}	330	MW
$c^{f,bp}$	19.3	€/MWh
$c^{f,ex}$	9.7	€/MWh
COP^{HP}	3	–
η^{bp}	1.1	–
η^{ex}	0.35	–
cb^{bp}	0.24	–
R^{bp}	50	MW/h
R^{ex}	40	MW/h
S^{flow}	300	MW/h
S^{loss}	1.05	MW/h
cv^{ex}	−0.12	–
cb^{ex}	0.64	–
$P^{min,bp}$	12	MW
$P^{min,ex}$	40	MW
$Q^{min,HP}$	10	MW
c^{su}	16,778	€
c^{sd}	116,778	€
$c^{su,HP}$	336	€
$c^{tax,coal}$	34.7	€/MWh
$c^{tariff,net}$	29.4	€/MWh
$c^{tax,el}$	55.3	€/MWh
c^{CO_2}	7.7	€/MWh
c^{NO_x}	1.2	€/MWh
$c^{bio,sup}$	20.1	€/MWh
c^{inf}	134.2	€/MWh
$r^{tax,f}$	1.2	–

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

that we can focus on the first weeks of February, May, August and November, which provide a representative sample of the yearly behavior of the system.

The remainder of this section presents four different case studies. These are primarily chosen in order to investigate the profitability of the HP and EB considering different technological setups and market conditions. Section 6.1 presents a comparison of the stochastic and the deterministic models, including an analysis of the impact of HP and EB capacity on the performance of the two models. Sensitivity studies with respect to changes in capacity for the HP and the EB are presented in Section 6.2. Similarly, Sections 6.3 and 6.4 analyze the sensitivity of the results with respect to changes in the COP for the HP and in the electricity prices, respectively.

6.1. Case 1: Deterministic and stochastic model comparison

In this section, results obtained with the deterministic and stochastic operation models are compared. First, an example of the differences of daily operation is provided, followed by an assessment of the difference in performance over the entire year 2013.

6.1.1. Daily production comparison

We now provide an example illustrating the differences in how the deterministic and the stochastic models adjust the production to meet the realized demand. Let us consider a particular scenario in the set sampled as described in Section 5. In this scenario, the heat demand is rather high, and in particular it is larger than as initially forecasted. Figs. 3 and 4 show the actual production for each unit as resulting from the stochastic and the deterministic model, respectively. Furthermore, the expected forecast values for heat demand and spot price are included in the figure along with their actual realization in the specific scenario. For the stochastic model, the actual production corresponds to the optimal readjustment of the recourse variables for heat production in the particular scenario considered. For the deterministic model, it can be determined by running the stochastic model with all first-stage variables fixed to the deterministic solution.

A significant difference between the two models is the occurrence of uncovered demand in the results from deterministic model, as illustrated by the brown area in Fig. 4. This is generally very undesirable, as it might lead to the start-up of expensive backup units or, even worse, to the curtailment of load. This occurs because the deterministic model overlooks the recourse stage when optimizing the day-ahead dispatch, as explained in Section 4. In this case, this myopic approach results in a pre-dispatch that is too inflexible to cope with the uncertain heat demand.

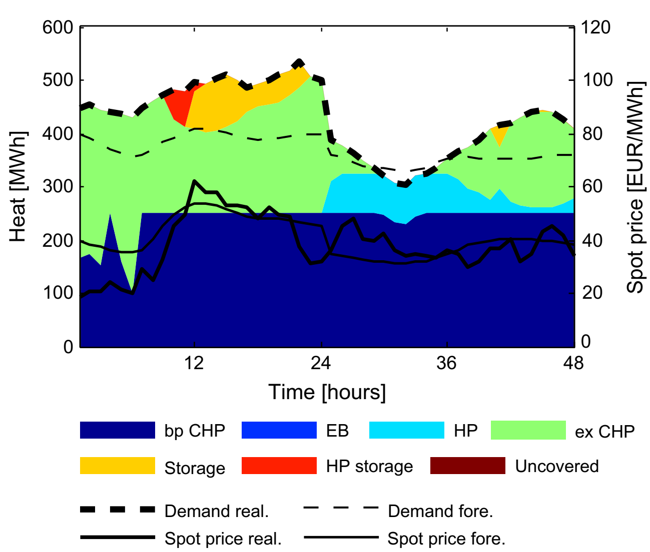

Fig. 3. Actual heat production for the stochastic solution in a scenario where realization of heat demand is larger than forecast.

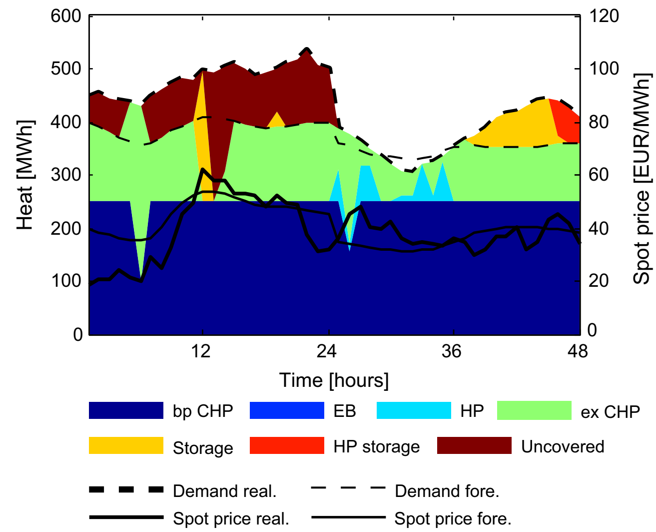

Fig. 4. Actual heat production for the deterministic solution in a scenario where realization of heat demand is larger than forecast.

6.1.2. Yearly economic assessment

In this section we compare the economic benefits of the stochastic and the deterministic models over a year. This is done by considering the average cost obtained with the respective solutions in the scenario set built as described in Section 5. In order to determine the average cost of the deterministic approach, we fix its solution as the day-ahead dispatch in the stochastic model. Subsequently, this model is solved, yielding the optimal recourse for the deterministic model.

Fig. 5 shows the total daily heat costs for the first week of February, May, August and November with the deterministic and the stochastic solutions. The relative difference in average weekly costs between the two models is found to be as follows:

$$w_{Feb} = 4\%, \quad w_{May} = 15\% \tag{43}$$

$$w_{Aug} = 22\%, \quad w_{Nov} = 4\% \tag{44}$$

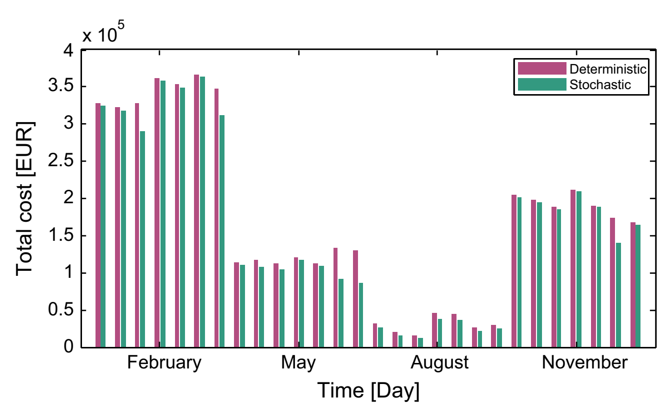

Fig. 5. Average cost for the deterministic and stochastic models.

The reason for the relatively small percentages in February and November is the high degree of flexibility in the dispatch of the system. In Section 5 the standard deviation of the heat demand was found to be $\sigma_\epsilon = 26.66$ MWh. As this standard deviation is small relative to the capacity of the HP and EB, the system is flexible enough for the deterministic model to handle the deviations almost as well as the stochastic optimization model. In May and August, the demand is very low and the back-pressure CHP is basically the only unit used for heat production. In this situation, the flexibility is limited and thus a higher benefit from using the stochastic model is observed.

6.1.3. Impact of HP and EB capacity

We now investigate how different HP and EB capacities impact the ability of the stochastic programming model to deliver lower average costs than the deterministic model. The following setups are considered:

1. 100% capacity for both the HP and EB (reference case 0).
2. 50% capacity for both the HP and EB.
3. 0% capacity for both the HP and EB.

A comparison of the three cases is displayed in Fig. 6. For each setup and week, the difference between the deterministic and the stochastic model results are found as a percentage of the cost obtained with the stochastic model. Thus, a positive difference implies that the stochastic model provides lower heat costs compared to the deterministic one.

For February and November, a small relative difference in performance is observed in the case of full HP and EB capacity. Indeed, the higher demand during these months forces many production units to operate simultaneously, which increases the flexibility of the system. Notably, the benefit of using a stochastic approach increases as the capacity of HP and EB is reduced. In particular, when the capacity for the EB and HP is fixed to zero, i.e., if the HP and EB are removed from the system, the stochastic solution is significantly better than the deterministic. In May and August the added benefit from using the stochastic model is generally higher, although it decreases in August when the capacity is decreased. This is likely due to the low heat demand during this month and the consequent exclusive use of the back-pressure CHP unit. The stochastic approach utilizes the HP and EB to increase the flexibility of the system. Hence, removing these units results in a larger cost increase for the stochastic model.

This analysis indicates that part of the gain in flexibility and in reduced costs obtained by installing HPs and EBs can actually be reaped just by employing stochastic programming to dispatch the system. Clearly, switching to stochastic programming is preferable to installing larger EB and HP capacity, as the capital cost for installing these units is significant. These results also imply that making an investment decision based on deterministic operational models runs the risk of overestimating the needed capacity and thus of being suboptimal.

6.2. Case 2: Reduction in HP and EB capacity

This section investigates the impact of reducing the HP and EB capacity, investigating the same cases considered in Section 6.1.3. Differently from that section, the purpose here is to assess the impact on system cost for the stochastic model only.

In the reference case 0, a heat capacity of 75 MW is used for both the EB and HP. This size, although relatively large, is realistically achievable. However, it is not necessarily the most optimal size. As the investment cost depends strongly on the size of the units, it is important to find the optimal capacity.

Fig. 7 shows a comparison of the results obtained by solving the stochastic programming model using the different capacities. For each of the considered weeks, the average daily heat costs are displayed. The results indicate a non-linear relationship between HP and EB capacity and the system costs. The difference also appears to be largest in February and November, which is the period where these units are utilized the most.

The yearly monetary savings having 50% and 100% capacity as opposed to 0% is estimated using a linear scaling of the result for the four representative weeks:

$$z_{0\%} - z_{50\%} = €2.5\text{ M}$$
$$z_{0\%} - z_{100\%} = €3.1\text{ M}$$

This corresponds to cost reductions of 4% and 5% compared to the zero capacity case.

The benefit of doubling the capacity from 50% to 100% results in a cost reduction of €3.1 M − €2.5 M = €0.6 M.

Notably, the first increase in capacity from 0% to 50% is more significant than the additional capacity from 50% to 100%. In order to formulate an appropriate investment strategy, such figures should be evaluated against the investment costs for units of different sizes. Indeed, both the benefit and the investment cost per MW decrease for these units. The former fact is proved by our results, while the latter results from economies of scale [39].

6.3. Case 3: Change in COP for HP

In the reference study (case 0) the COP for the HP was set to $COP^{HP} = 3.0$. However, both higher and lower values for the COP

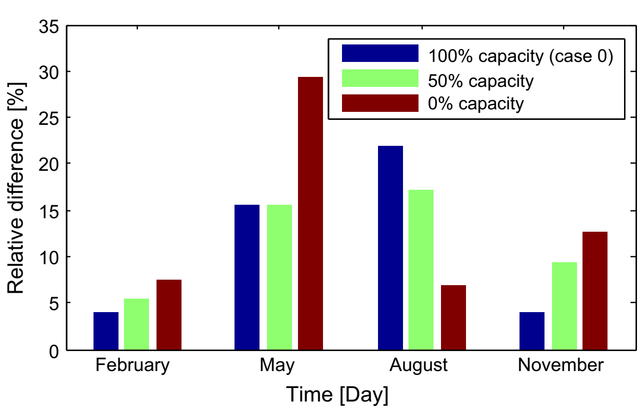

Fig. 6. Improvement in average cost obtained by switching from the deterministic to the stochastic model.

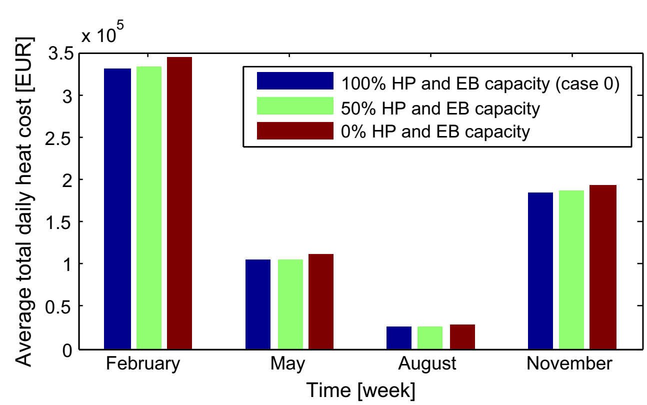

Fig. 7. Average daily system costs for different HP and EB capacities.

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

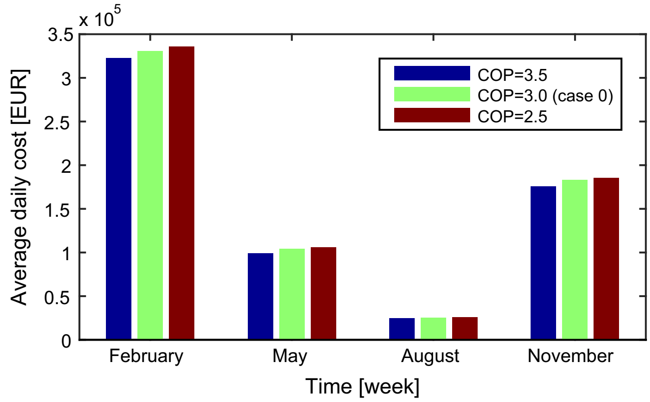

Fig. 8. Average daily system cost for different values of COP for the heat pump.

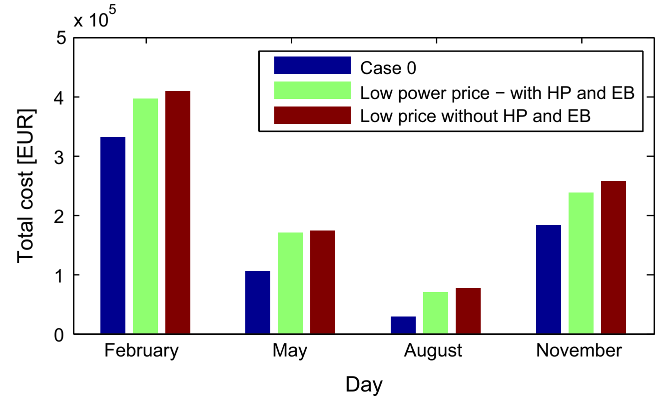

Fig. 9. Average daily heat costs with and without HP and EB capacity if the electricity prices are decreased by 10 €/MWh.

could occur depending on the characteristics of the HP and the choice of the cold heat source [40,41].

In this section we assess the impact on the system cost resulting from increasing and reducing the COP to 3.5 and 2.5, respectively. This study is particularly relevant as the COP fluctuates over the year due to varying temperature requirements or variations in the cold source temperature [8]. Fig. 8 shows a comparison of daily average heat cost with a COP of 2.5, 3.0 and 3.5.

The yearly monetary savings are here averaged to be:

$$z_{COP=2.5} - z_{COP=3} = €0.9\text{ M}$$
$$z_{COP=3.5} - z_{COP=3} = -€1.9\text{ M}$$

These results can be used as input to the decision-making process concerning the choice of HP technology and characteristics. If an increase in COP from 3.0 to 3.5 is achievable at costs similar to the yearly costs outlined above, the payback time for this additional investment is one year.

6.4. Case 4: Electricity price decrease

In this section we investigate the case of decreasing electricity prices. This is particularly interesting, as increasing shares of wind power in the electricity production will bring about lower power prices on average. Low electricity prices will in reality usually occur when there is a high wind power penetration [35]. However, for simplicity we assume that all electricity prices are lowered by a constant amount. This allows for a study of the electricity price impact on the economic benefits of HPs and EBs. Two cases characterized by lower electricity prices are investigated along with the reference case. In one of the additional cases, the system includes neither heat pumps nor electric boilers, while in the other we consider the same capacity as in the reference case for these units. The two additional cases are characterized by the following parameters:

1. $p_{t,\xi}^{spot,red} = p_{t,\xi}^{spot} - 10\,€/\text{MWh}$
   $C^{HP} = C^{EB} = 75\text{ MW}$
2. $p_{t,\xi}^{spot,red} = p_{t,\xi}^{spot} - 10\,€/\text{MWh}$
   $C^{HP} = C^{EB} = 0\text{ MW}$

Fig. 9 shows the average daily system costs in the two cases compared to the reference case 0. If the electricity prices drop on average, a significant increase in the total cost is observed. This can be explained from the high forced production of power at the CHP plants which is sold at a lower price.

The yearly savings resulting from the installation of an HP and EB in the case that the spot price decreases by 10 €/MWh amount to

$$z_{power,100\%} - z_{power,0\%} = €4.1\text{ M}$$

This result indicates that a significant increase, from €3.1 M to €4.1 M, in the economic value of HPs and EBs is obtained in the event of decreasing power prices. When considering a potential investment in HPs and EBs, the future evolution of power prices should be carefully assessed, as these will most likely reach lower levels with increasing wind power penetration. We leave as a direction of future work the assessment of the value of HPs and EBs when the power prices, rather than decreasing uniformly, drop as a function of wind power production.

7. Conclusion

This paper presents an assessment of the economic value of electric boilers and heat pumps in the Danish energy system. This assessment is performed by simulating the financial performance of optimization models that mimic the decision-making process conducted daily by utilities to dispatch and trade the output of their units on the heat and power markets. The setup of our study is specifically tailored to the Danish case of the Greater Copenhagen area, considering realistic unit data and the currently existing tax scheme, which is shown to have a significant impact on the merit-order of the production units. The case of Denmark is particularly relevant, because the small Nordic country is a frontrunner in the integration of heat and power systems with the ambitious goal of having fully renewable heat and power systems by 2035. Therefore, Denmark may set an example for other countries with a high share of fluctuating renewable power resources and district heating. For example, China is currently investing in wind power generation a lot and the country is already facing important wind power curtailment due to the inflexibility of its power grid. In some provinces in China, the curtailment rate amounts to 20% of the generated wind power. A recent study entitled "System integration of wind power by use of the DH/CHP systems in northeast China" [42] analyzes how district heating systems can help reduce the need for wind power curtailment by, e.g., using surplus electricity in heat pumps and electric boilers. In this vein, the presented models can be easily adapted to other energy systems existing worldwide.

Two models for optimizing the day-ahead dispatch and trade of the outputs of heat pumps, electric boilers and combined heat and power plants are developed in this paper. The first model consists in a deterministic optimization of the system solely based on a

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

point forecast (expected value) for the uncertain heat demand and power prices. Furthermore, a more advanced model based on stochastic programming is developed to account for the uncertainty involved in such forecasts through the use of scenarios representing plausible future paths of heat demand and power prices.

A comparison of the financial results obtained from the deterministic and the stochastic programming models shows that the difference in performance is large when a small capacity of heat pumps and electrical boilers is applied, but it decreases sharply with the installed capacity. This has two important implications. Firstly, part of the potential cost savings from investing in heat pumps and electric boilers can be obtained by using more advanced operational strategies accounting for system uncertainty. The implementation of the latter has much lower capital cost than investing in new units. Secondly, the use of deterministic operational models should be avoided when making decisions on investment in heat pumps and electric boilers. Indeed, this may result in an overestimation of the value of these units, and hence in a suboptimal decision on the capacity to be installed.

A series of sensitivity studies is presented using the stochastic operational model in order to evaluate the impact of different technological and market parameters on the economic potential of heat pumps and electric boilers. The investigated cases include reduction in HP and EB capacity, change in the coefficient of performance for the heat pump as well as a decrease in power prices. The results confirm that the considered parameters are of great importance, as they show savings in the range between €0.9 M and €4.1 M per year. The largest economic value is obtained in the case of low electricity prices. This is of particular importance as it is believed that the planned increase in the share of wind in the Danish electricity production mix will result in lower power prices. Hence, heat pumps and electric boilers could increase their profitability in the future.

This work opens up a number of directions for future research. One could extend the forecasting models for heat demand and power prices including, e.g., wind power as an explanatory variable. Furthermore, the stochastic programming model could be upgraded to include additional market stages, e.g., capacity markets or the intra-day and the balancing markets for electricity.

Finally, the achievement of a fully renewable Danish energy system will not be without a physical and economic transformation of the Danish energy sector [43]. Naturally, this will compel us to update the economic valuation carried out in this paper and revise the conclusions drawn from it as changes take place. For example, electric batteries and electric vehicles could also play an important role in the fully or predominantly renewable energy systems of the future and as such, should be taken into account in studies aimed at unveiling the evolution of the energy mix. For the time being, though, electric storages are still under development, very costly, and not commercially available in large sizes. Electric cars are expected to be gradually introduced, but their contribution to the system flexibility depends on the successful development and implementation of smart-grid technologies that make it possible to schedule their charging according to the system conditions (e.g., the electricity price) [44]. Likewise, the production and use of hydrogen could also contribute to the large-scale integration of fluctuating renewable energy sources in a longer term. Power surplus from fluctuating renewables could be utilized to produce and store hydrogen for later use for electricity generation or in hydrogen-fueled vehicles. Much development within this area is, however, still ongoing, and the required technology is not commercially available yet, with important challenges regarding costs-effectiveness and energy efficiency to be addressed. Heat pumps and electric boilers in the district heating system are, on the contrary, comparatively well-established technologies whose operation is, besides, centrally optimized by a utility company on the basis of the variations of the electricity price. This justifies the relevance of economic analyses such as the one conducted in this paper.

Acknowledgements

The work of the authors is partly funded by DSF (Det Strategiske Forskningsråd) through the CITIES (No. 1035-00027B) project, which is hereby acknowledged. M. Zugno and J.M. Morales also thank the ENSYMORA (No. 10-093904) project for the financial support. The authors are grateful to H.Aa. Nielsen from ENFOR, D. Andersen from Varmelast.dk, J. Boldt, H. Damgaard and J.H. Nielsen from HOFOR for supporting with data and/or discussions.

References

[1] The Danish Government. Vores energi; 2012. <http://ens.dk>.
[2] Meibom P, Hilger KB, Madsen H, Vinther D. Energy comes together in Denmark. IEEE Power Energy Mag 2013.
[3] Mathiesen B, Lund H, Connolly D, Wenzel H, Østergaard P, Möller B, et al. Smart energy systems for coherent 100% renewable energy and transport solutions. Appl Energy 2015;145:139–54.
[4] Danish Energy Agency. Energy statistics, 2012; 2013. <http://ens.dk>.
[5] Jónsson T, Pinson P, Madsen H. On the market impact of wind energy forecasts. Energy Econ 2010;32(2):313–20.
[6] Lund H, Münster E. Integrated energy systems and local energy markets. Energy Policy 2006;34(10):1152–60.
[7] Nielsen M.G. Probabilistic forecasting and optimization in CHP systems. Master's thesis. Technical University of Denmark; 2014.
[8] Bach B. Integration of heat pumps in greater Copenhagen. Master's thesis. Technical University of Denmark; 2014.
[9] Dansk Energi. Mulighederne for den fremtidige fjernvarmeproduction i decentrale områder, analyse nr. 9; December 2013.
[10] Lund H. Large-scale integration of wind power into different energy systems. Energy 2005;30(13):2402–12.
[11] Aringhieri R, Malucelli F. Optimal operations management and network planning of a district heating system with a combined heat and power plant. Ann Oper Res 2003;120.
[12] Rolfsman B. Combined heat-and-power plants and district heating in a deregulated electricity market. Appl Energy 2004;78(1):37–52.
[13] EMD International A/S. energyPRO; July 2015. <http://www.emd.dk/energypro/>.
[14] Birge JR, Louveaux F. Introduction to stochastic programming. Springer series in operations research and financial engineering. Springer; 2011.
[15] Dimoulkas I, Amelin M. Constructing bidding curves for a CHP producer in day-ahead electricity markets. In: 2014 IEEE International Energy Conference (EnergyCon), Dubrovnik, Croatia; 2014. p. 487–94.
[16] De Ridder F, Claessens B. A trading strategy for industrial CHPs on multiple power markets. Int Trans Electr Energy Syst 2014;24(5):677–97.
[17] Zugno M, Morales JM, Madsen H. Robust management of combined heat and power systems via linear decision rules. In: 2014 IEEE international energy conference (EnergyCon), Dubrovnik, Croatia; 2014. p. 479–86.
[18] Zapata J, Vandewalle J, D'haeseleer W. A comparative study of imbalance reduction strategies for virtual power plant operation. Appl Therm Eng 2014;71(2):847–57.
[19] Ravn H. Balmorel: a model for analysis of the electricity and CPH markets in the baltic sea region; 2010. <http://balmorel.com/documents.html>.
[20] Lund R, Mathiesen BV. Large combined heat and power plants in sustainable energy systems. Appl Energy 2015;142:389–95.
[21] Blarke MB, Dotzauer E. Intermittency-friendly and high-efficiency cogeneration: operational optimisation of cogeneration with compression heat pump, flue gas heat recovery, and intermediate cold storage. Energy 2011;36(12):6867–78.
[22] Hendriksen NP. Utilization of waste heat from the industry. Master's thesis. Technical University of Denmark; 2014.
[23] Meibom P, Kiviluma J, Barth R, Brand H, Weber C, Largsen H. Value of electric heat boilers and heat pumps for wind power integration. Wind Energy 2007.
[24] Morales JM, Conejo AJ, Madsen H, Pinson P, Zugno M. Integrating renewables in electricity markets: operational problems. International series in operations research and management science, vol. 205. New York (USA): Springer; 2014.
[25] Pandžić H, Morales JM, Conejo AJ, Kuzle I. Offering model for a virtual power plant based on stochastic programming. Appl Energy 2013;105:282–92.
[26] HOFOR; November 2014. <http://hofor.dk/amagervaerket/vaerket/>.
[27] EA Energianalyse. Afgifter på varmepumper til fjernvarme; 2010. <http://ea-energianalyse.dk/reports/929_Afgifter_varmepumper.pdf>.
[28] The Danish Ministry of Taxation. Analyse nr. 9; December 2013.
[29] Nord Pool Spot; February 2014. <http://nordpoolspot.com/TAS/Day-ahead-market-Elspot/>.
[30] Conejo AJ, Carrion M, Morales JM. Decision making under uncertainty in electricity markets. International series in operations research & management science, vol. 153. New York (USA): Springer; 2010.

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115

[31] Lund H, Andersen AN, stergaard PA, Mathiesen BV, Connolly D. From electricity smart grids to smart energy systems – a market operation based approach and understanding. Energy 2012;42(1):96–102.
[32] Varmelast; February 2014. <http://varmelast.dk/da/varmeplaner/varmeplaner>.
[33] SKAT; January 2014. <https://www.skat.dk/SKAT.aspx?oID=2049002>.
[34] Jónsson T, Pinson P, Nielsen HA, Madsen H, Nielsen TS. Forecasting electricity spot prices accounting for wind power predictions. IEEE Trans Sust Energy 2013;4(1):210–8.
[35] Gil HA, Lin J. Wind power and electricity prices at the PJM market. IEEE Trans Power Syst 2013;28(4):3945–53.
[36] Madsen H. Time series analysis. Chapman & Hall; 2008.
[37] Energinet.dk; February 2014. <http://energinet.dk>.
[38] CPLEX Website; November 2014. <http://www-01.ibm.com/ software/commerce/optimization/cplex-optimizer/>.
[39] Danish Energy Agency. Technology data for electricity, district heating, energy storage and energy conversion; 2014.
[40] HOFOR. Varmepumper i fjernvarmesystemet; 2013.
[41] Industrial Heat Pumps; June 2014. <http://www.industrialheatpumps.nl/en/how_it_works/cop_heat_pump/>.
[42] Danish Energy Agency. System integration of wind power by use of the DH/CHP systems in north-east China – contributing to efficiently incorporating wind power into the system; July 2015. <http://www.ens.dk/sites/ens.dk/files/politik/Kina-samarbejdet/Materialer/Faktaark/harbin_eng.pdf>.
[43] Lund H, Werner S, Wiltshire R, Svendsen S, Thorsen JE, Hvelplund F, et al. 4th generation district heating (4GDH): integrating smart thermal grids into future sustainable energy systems. Energy 2014;68:1–11.
[44] Iversen EB, Morales JM, Madsen H. Optimal charging of an electric vehicle using a Markov decision process. Appl Energy 2014;123:1–12.

Please cite this article in press as: Nielsen MG et al. Economic valuation of heat pumps and electric boilers in the Danish energy system. Appl Energy (2015), http://dx.doi.org/10.1016/j.apenergy.2015.08.115