



# Optimization of combined heat and power production with heat storage based on sliding time window method



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## HIGHLIGHTS

- New sliding time window method for optimizing CHP with storages.
- The method benefits both design and operation of CHP systems.
- Simulation of the benefit of the method in practice.
- Optimization can lead to significantly larger revenue from power sales.
- The method can be used to optimize the size of new heat storage.

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## ABSTRACT

A combined heat and power (CHP) optimization model with heat storage is proposed to minimize the production cost and to maximize the revenue from power sales based on a sliding time window method. The model can be applied both for operating heat storage optimally and supporting investment planning for a new storage. Heat demand is forecasted based on a weather forecast. Each day the heat demand and power price forecasts are input to a generic CHP optimization model for a several-day time window to obtain a heat storage operation plan. Then only the first day of the plan is implemented with actual power price and heat demand using a single-day optimization model to compute the actual production amount, fuel costs and revenue from power sales. After that, the time window is slid one day forward, and the above-mentioned process is repeated. In the test runs, forecasts for power price and temperature are simulated by disturbing actual (historical) data by the Wiener process (random walk). To evaluate the benefit and validate the proposed method, the results are compared with the no-storage case and the theoretical optimum assuming perfect demand and price forecasts. The results show that the revenue from power sales can be significantly improved. The method is used to evaluate the benefit of different sized storages for the CHP system. Also the effect of the width of the time windows on the performance of the method is evaluated. The model was tested using real-life heat demand data for the city of Espoo in Finland, and NordPool spot market data for power price for a one year time horizon. The results indicate that considering the forecasting uncertainty, 5-day sliding time window method can obtain 90% of the theoretically possible cost savings that can be derived based on perfect forecasts.

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## 1. Introduction

Combined heat and power (CHP) is a booming technology which simultaneously produces heat and power by recovering heat that would otherwise be wasted in conventional condensing generation of electric power. Since 2007, the European Council has targeted to tackle several serious climate change and energy related

issues. In details: 20% CO<sub>2</sub> emissions reduction comparing to 1990; 20% improvement in energy efficiency; 20% share of renewable energy sources in the end-use, which is called 20–20–20 goals, should be acquired by 2020 [1]. CHP is considered a sustainable and economic technology to fulfill those abovementioned goals for its significant performance in fuel demand reduction, greenhouse gas reduction and fossil fuel independency [2]. For instance, biomass-fired CHP plants are technically and economically advantageous for carbon emission reduction given the proper system efficiencies, fuel costs, incentives, thermal energy usage, etc. For small scale CHP, Micro-CHP units are considered to replace

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## Nomenclature

### Indices and index sets

$J$	the set of extreme points of the operating region of CHP plant
$j$	index of extreme point in characteristic
$t$	time index (h) within time horizon

### Variables

$x_j^t$	to encode the operating region of the CHP plant as a convex combination
$s_q^t$	the heat storage content at hour $t$ (MW h)
$q_{s+}^t$	the amount of charged heat at hour $t$ (MW h)
$q_{s-}^t$	the amount of discharged heat at hour $t$ (MW h)
$q_{hob}^t$	The heat production by heat only boiler at hour $t$ (MW h)

### Parameters

$c_p^t$	the spot price of power at hour $t$ (€/MW h)
$c_{hob}^t$	the fuel cost for heat only boiler at hour $t$ (€/MW h)
$c_j$	fuel cost at the CHP characteristic point $j \in J$ (€/MW h)
$p_j$	power production at the CHP characteristic point $j \in J$ (MW h)
$q_j$	heat production at the CHP characteristic point $j \in J$ (MW h)
$Q^t$	heat demand at hour $t$ (MW h)
$s_q^{max}$	heat storage capacity (MW h)
$s_{q+}^{max}$	maximum heat storage charging power (MW h)
$s_{q-}^{max}$	maximum heat storage discharging power (MW h)
$T$	the last time step
$\eta_{s-}$	efficiency ratio for heat charge–discharge cycle
$\eta_s$	efficiency ratio heat storage per hour

conventional boilers in home installations. The production of electricity simultaneously with the generation of heat yields an economic benefit for the user. Also, the fossil fuel consumption and CO<sub>2</sub>-emissions are effectively lowered. These good performances for micro-CHP are evaluated in [3,4]. CHP has been widely utilized due to the liberalization of the power market, the rise in fuel prices, the improvements in CHP technology, tax exemptions when CHP is adopted, the introduction of environmental restrictions from both municipal and central governments [5]. The thermal and electrical efficiency depend on the operating point (loading conditions), unit capacity and technology [6]. The economic benefits of CHP systems depend on the specific conditions under different operation strategies, as the performance varies when operating in partial load [6,7]. When all the thermal energy of a CHP system can be utilized, it can reach much higher efficiency than conventional separate heat and power production [8]. CHP fits well in applications like industries, which have constant thermal demands. CHP has also been applied successfully for applications which have time-varying demand of thermal energy, such as municipal district heating and cooling systems, and even small scale applications for residential buildings, office buildings, hospitals, supermarkets, etc. [3]. Finland is one of the leading countries in CHP production due to its cold climate and energy-intensive metal and forest industries. CHP generates around 34% of the power in Finland [9]. Optimization of CHP production can result in a considerable savings. The target of the optimization is to satisfy customers' demand of heat while minimizing the production costs and maximizing the revenue from selling power. The time horizon of an optimization model can vary from a few hours up to several years.

Heat storage which collects heat for later use can be integrated into a CHP system to further improve the energy efficiency [10]. On one hand, the storage can be charged when the heat demand is low and discharged during high demand; on the other hand the storage allows increasing the power production by CHP to the power market when the spot price is high and producing less power when the spot price is low. Thus, the heat storage can be charged or discharged when either one is beneficial. The flexibility of the heat demand allows developing algorithm to optimally control the coupling between decentralized energy resources and heat storage in order to achieve economical and practical benefits for the CHP system [11]. Without storage the operation of CHP plants mainly depends on the current heat demand and thus determines the range of power production. Heat storage can decouple the heat production and allow for price-driven power production. To decrease the operational fallibility of the CHP plants, heat storage

is used to maximize the operation of CHP units when heat demand is even smaller or larger than operational capacity of the CHP plants.

The cost efficient solutions about CHP system with heat storage have been discussed in many recent studies. Christidis et al. [12] optimized the design of heat storage devices together with the operation of a power plant supplying a large district heating network by formulating a mixed integer linear programming (MILP) problem in GAMS and solving it in CPLEX. Fragaki et al. [13] analyzed the economics and optimum size of a CHP system operating with gas engines and thermal stores in British market conditions using energyPRO software. Fragaki and Andersen [14] optimized the timing of power sale at the power exchange market for a CHP system with heat storage in the UK using energyPRO software and Excel spreadsheets. Chesi et al. [15] optimized the heat storage size using a TRNSYS unsteady model in the context of combined cooling, heating and power (CCHP) with renewable energy source. Ren et al. [16] optimized the size of CHP system with a heat storage using mixed integer non-linear programming model. Buoro et al. [17] explored the optimal operation strategy in order to minimize the total annual cost based on a mixed integer linear programming (MILP) model for a distributed energy supply system including a CHP plant, a DH network, a solar thermal plant and conventional components such as boilers and compression chillers. Taljan et al. [18] optimized the operation of biomass CHP plant and the heat storage subject to maximizing the economic index in form of modified internal rate of return (MIRR). Noussan et al. [19] searched the optimal configuration by simulating a biomass-fired CHP and heat storage system from economic and energetic point of view. Steen et al. [20] proposed a new Distributed Energy Resources Customer Adoption Model (DER-CAM) with thermal energy storage to minimize the energy cost or CO<sub>2</sub> emissions using mixed integer linear programming (MILP). Barbieri et al. [21] assessed the influence of the thermal energy storage on the energy and economic performance of a CHP system consisting of a prime mover, an auxiliary boiler and a storage unit. The effect of the size of the thermal energy storage is not linear and is heavier by increasing the thermal power of the prime mover. Smith et al. [22] investigated the performance of a CHP system with and without thermal energy storage for eight different commercial building types, the model evaluated which types of commercial buildings may show benefits from adding the heat storage to the CHP systems and which types are unlikely to benefit from the addition of heat storage. However, no studies were done to achieve the optimal operation plan for the CHP system with heat storage by

considering the uncertainty of forecasts for heat demand and power price.

The past studies have optimized the production assuming perfect information for the planning horizon. In this study we consider the uncertainty of the forecasts in a two stage process of first optimizing the operative plan with a longer time window (multiple days) against uncertain forecasts and then implementing the initial part (first day) of the plan based on actual demand and price. The advantage of this approach is that the operational plan for the coming day considers the forecasting information for the entire time window.

In this paper, we propose an hourly dynamic model which optimizes the net operating cost of a backpressure CHP plant with a heat-only boiler (HOB) and short-term heat storage based on inaccurate forecasts for power price and heat demand from the techno-economic point of view. The key decision in the planning problem is how to operate the heat storage. The CHP production and the HOB production will be simultaneously optimized by our CHP planning model. We apply our previously designed heat demand forecasting model [23] to predict the heat demand based on outdoor temperature forecast. We simulate the forecasts for outdoor temperature and electricity price by disturbing the actual hourly time-varying historical data based on the Wiener process. To plan how to operate the heat storage, we apply a 5-day sliding time window method which aims to seek the most cost-efficient operation of the CHP system. This paper focuses on the operation of the CHP system with fixed unit commitment. We demonstrate the method using real-life data for heat demand and outdoor temperature for the second largest Finnish city Espoo, which is located next to the capital Helsinki in Southern Finland. For power price we use NordPool spot market area price for Finland [24]. To validate and evaluate the efficiency of the method, we compare the results with the no-storage case (0-size storage) and the theoretical optimal solution computed based on perfectly accurate demand and price forecasts.

The novelty of this study is stressed as follows:

- Optimizing the operational planning (dispatch strategy and net operating cost) between the CHP and heat storage based on hourly heat demand and power price forecasting.
- Sliding time window method on top of a generic CHP optimization model is applied to improve the accuracy of the model by having the vision of the near future.
- Sliding time window method considers the uncertainty of forecasts for heat demand and power price.
- The method is compared with both no-storage and theoretical case to understand its cost efficiency.
- The effect of the width of the time window on the performance of the method is analyzed.
- The net operating cost as a function of the storage size is found.
- The energy efficiency of the overall CHP system as a function of storage size is found.
- An hourly dynamic model is considered for one year time horizon using real-life data.

The rest of this paper is structured as follows: Section 2 presents the sliding time window method that is used to optimize the CHP production and storage operation. The computational results are shown in Section 3. Section 4 discusses the effect of the width of the time window and the storage size on the optimal net operating costs. Section 5 presents the effect of the storage size on the overall energy efficiency. Finally the paper is concluded in Section 6.

## 2. Methods

The sliding time window method is implemented in two phases. In the first phase a multi-period CHP planning model is

solved for a several-day time horizon based on heat demand and power price forecasts. In the second phase the plan for storage operation is implemented for the first day based on actual heat demand and power price. The CHP model and the sliding time window method are described in the following sections. The model has been implemented using Matlab and the LP2 solver [25] for solving the LP problems.

### 2.1. The CHP model

The CHP planning model is a multi-period linear programming (LP) model consisting of hourly CHP models connected together by storage constraints. The hourly characteristic operating region of a CHP plant can be considered as a surface in 3-dimensional space (see Fig. 1), corresponding to different combinations of heat and power production ( $p, q$ ) and production cost  $c$ . This generic representation is valid for all CHP technologies. By assuming that the CHP characteristic is convex, the feasible operating region in the ( $p, q$ ) plane is convex, and the production cost is a convex function of  $p$  and  $q$ . The assumption of convexity is reasonable for many types of CHP plants [25,26]. However, with more complex combi-plant technologies and in part load modes, the characteristic may be non-linear and non-convex. Mixed integer encoding of the plant characteristic can be applied when convexity cannot be assumed [27,28]. However, this is out of the scope of this paper.

Assuming that the CHP characteristic is convex, the relationship between the production level of heat and power, and the hourly operating costs ( $Q, P, C$ ) of a CHP plant can be represented as the convex combination of corner points of the plant characteristic ( $q_i, p_i, c_i$ )

$$\begin{aligned} C &= \sum_{j \in J} c_j x_j \\ P &= \sum_{j \in J} p_j x_j \\ Q &= \sum_{j \in J} q_j x_j \\ \sum_{j \in J} x_j &= 1 \\ x_j &\geq 0, j \in J \end{aligned} \quad (1)$$

where  $c_j$  is the production cost,  $p_j$  is the net power production, and  $q_j$  is the net heat production at the characteristic point  $j \in J$ ,  $j$  is the subscript of extreme point in characteristic, and  $J$  is the set of extreme points of the operating region of the plant.  $P$  is the net power production,  $Q$  is net heat production and  $C$  is the production cost. Net heat and power production means that any self-

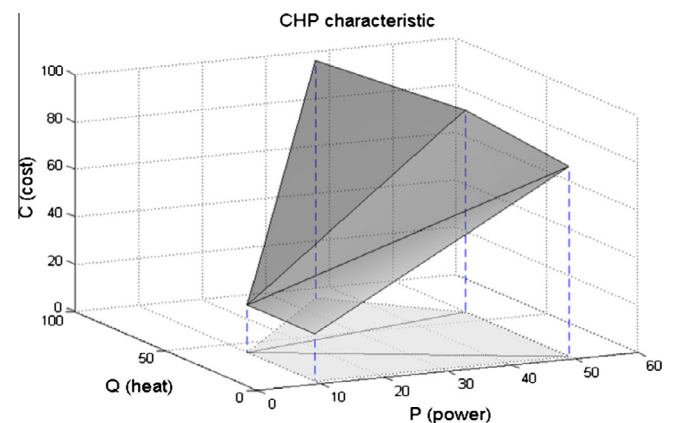


Fig. 1. Operating region of a convex CHP plant [25].

consumption of energy has been excluded. Production costs consist mainly of fuel costs, but can include other variable costs that depend on production amount, such as maintenance costs. The  $x$ -variables are used to encode the operating region as a convex combination. A convex combination is a weighted average of characteristic points with non-negative weights. For simplicity, the time index  $t$  is excluded from the hourly CHP model.

The multi-period CHP planning model is composed of hourly CHP models connected together by storage constraints. The CHP model used in this study contains a single back pressure CHP plant, one HOB and one heat storage. However, the model can be easily extended to contain multiple CHP plants, HOBs and storages. The objective is to minimize the overall net operating costs as follows:

$$\min \sum_{t=1}^T \left( \left( \sum_{j \in J} c_j^t x_j^t \right) + c_{hob}^t q_{hob}^t - c_p^t P^t \right) \quad (2)$$

$$\sum_{j \in J} x_j^t = 1 \quad (3)$$

$$\sum_{j \in J} p_j^t x_j^t = P^t \quad (4)$$

$$\sum_{j \in J} q_j^t x_j^t - q_{s+}^t + \eta_{s-} q_{s-}^t + q_{hob}^t \geq Q^t \quad (5)$$

$$s_q^t = \eta_{s+} s_q^{t-1} + q_{s+}^t - q_{s-}^t \quad (6)$$

$$\begin{aligned} 0 &\leq s_q^t \leq s_q^{max} \\ 0 &\leq q_{s+}^t \leq q_{s+}^{max} \\ 0 &\leq q_{s-}^t \leq q_{s-}^{max} \\ x_j^t &\geq 0 \\ t &= 1, \dots, T \end{aligned}$$

Here  $c_p^t$  is the spot price of power at hour  $t$ ,  $s_q^t$  is the heat storage content,  $q_{s+}^t$  and  $q_{s-}^t$  are the amounts of heat charged and discharged,  $s_q^{max}$  is the heat storage capacity,  $\eta_{s-}$  is the efficiency ratio for discharging heat from the storage,  $\eta_{s+}$  is the efficiency ratio for storing heat for one hour,  $q_{hob}^t$  is the heat production by the HOB, and  $T$  is the last time step. Different kinds of heat storages, for example a pressurized hot water tank can be modeled in terms of three parameters  $s_q^{max}$ ,  $\eta_{s-}$ , and  $\eta_{s+}$ .

The objective function (2) minimizes the overall net operating costs including production costs  $c^t$  subtracted by the revenue of selling the produced power  $P^t$  at the price  $c_p^t$  to the power market.

**Table 1**  
Operating points and parameters.

Heat demand	Hourly heat demand of city of Espoo, Finland for the year 2014, totally 2252628.741 MW h
Power price	Hourly NordPool spot price for the year 2014 (€/MW h)
Capacity of CHP plant	Heat = 800 MW Power = 350 MW Fuel = 1265 MW
Minimum CHP production rate	0
HOB capacity	1000 MW h
Fuel price for CHP plant	15 €/MW h
Fuel price for HOB	10 €/MW h
Storage capacity	3000 MW h (0–10 000 MW h)
Storage efficiency	0.9995
Discharge efficiency	0.99
The width of the sliding time window	5 days (1–8 days)

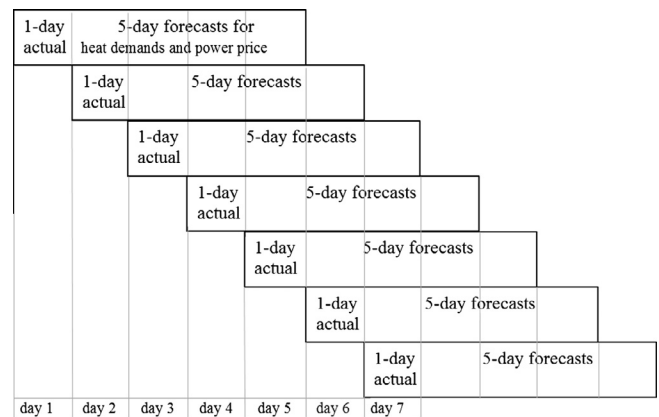
Observe that investment/capital costs and other non-variable costs are excluded from the objective function, because the optimal operation does not depend on any fixed costs. Eq. (4) is the power balance which determines the amount of produced power at each hour. Eq. (5) is the heat balance which states that the produced heat subtracted by the charged heat plus the discharged heat should satisfy the heat demand  $Q^t$  at each hour. This balance is written as an inequality constraint, meaning that an excess of heat may be produced and can be freely disposed. If excess heat cannot be freely disposed, a surplus variable with associated costs can be included in the model.

Table 1 summarizes the values of the parameters for the CHP model used in this study. In this study we apply a simple back pressure plant model defined in terms of the maximum production capacity for heat, power and fuel consumption, and the minimum CHP production rate. This means that the plant operates using a fixed power-to-heat ratio. The actual CHP plant of Espoo is more complex and flexible in its operation. The minimum production rate defines the fraction of the maximum production that the CHP plant can produce during an hour. Although the CHP plant would not run near zero production continuously, in transient situations where the plant is shut down or started up, the hourly production could be near zero. For this reason we have applied zero minimum production rate in the test runs. The fuel for the HOB is cheaper than for the CHP plant, but the profitability of using the CHP plant will benefit from selling the produced power to the market. The CHP plant is connected to a district heating system. The energy carrier is hot water.

## 2.2. Sliding time window method

The sliding time window method first determines the optimal operation of the CHP system including heat storage usage for a 5-day (120-h) time window based on forecasts for heat demand and power price. A 5-day time window was chosen because in real life, a moderately accurate heat demand forecast can be formed based on 5-day weather forecasts available from the meteorological institute. In Section 4.1 we also present tests for different widths of the time window.

Because forecasts are never perfectly accurate, the optimized plan cannot be implemented in reality, but must be adjusted according to the actual heat demand and power price. Therefore, in the second phase, we test how well the plan can be implemented. To do this, we solve the CHP production planning model for the first day of the time window with storage levels fixed based on the first day of the 5-day model and actual (historical) heat demand and power price. This is called the **day plan**. Then we slide



**Fig. 2.** 5-Day sliding window method for one week.

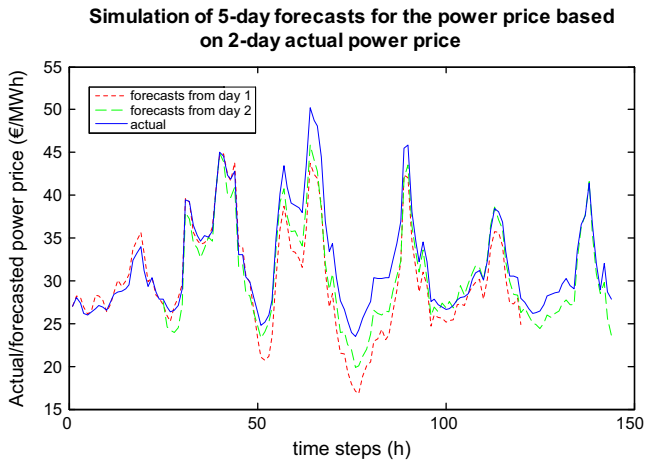


Fig. 3. Simulation of 5-day forecasts for the power sales price based on 2-day actual power price.

the time window one day ahead and repeat the process for the entire time horizon (1 year in this study). Fig. 2 illustrates the 5-day time window sliding process.

Table 2  
CHP models and input data.

Input	Model		
	Sliding time window method 5-day/dayplan model	Theoretical	No-storage
Heat demand	Forecasts/actual	Actual	Actual
Power price	Forecasts/actual	Actual	Actual
Heat storage	To be computed/planned storage	Initial value is 0, the rest are to be computed	0 all the time

When implementing the planned heat storage use for a day based on actual heat demand and power price, it is possible that sometimes the planned heat production exceeds the production capacity or is negative at that time step; this will result in an infeasible solution for the CHP model. Such plan cannot be implemented in practice either. To fix the problem, in such situations we adjust the heat production to be within feasible bounds and optimize storage level based on that.

2.3. Simulation of forecasts

In this study past forecasts were not available. Therefore, to simulate the inaccurate heat demand forecasts, we first form a simulated weather forecast by disturbing the actual historical weather (temperature) data based on a Wiener process (random walk). Then, from the weather forecast we form a heat demand forecast by applying our previously designed forecasting model [23]. The forecasting model is based on daily and weekly consumption rhythm and outdoor temperature. Similarly, to simulate the inaccurate power price forecasts, we disturb the actual historical NordPool spot price data [24] by another Wiener process. The Wiener process represents the integral of a Gaussian white noise process. The mean value of the forecasted error is 0. If the hourly

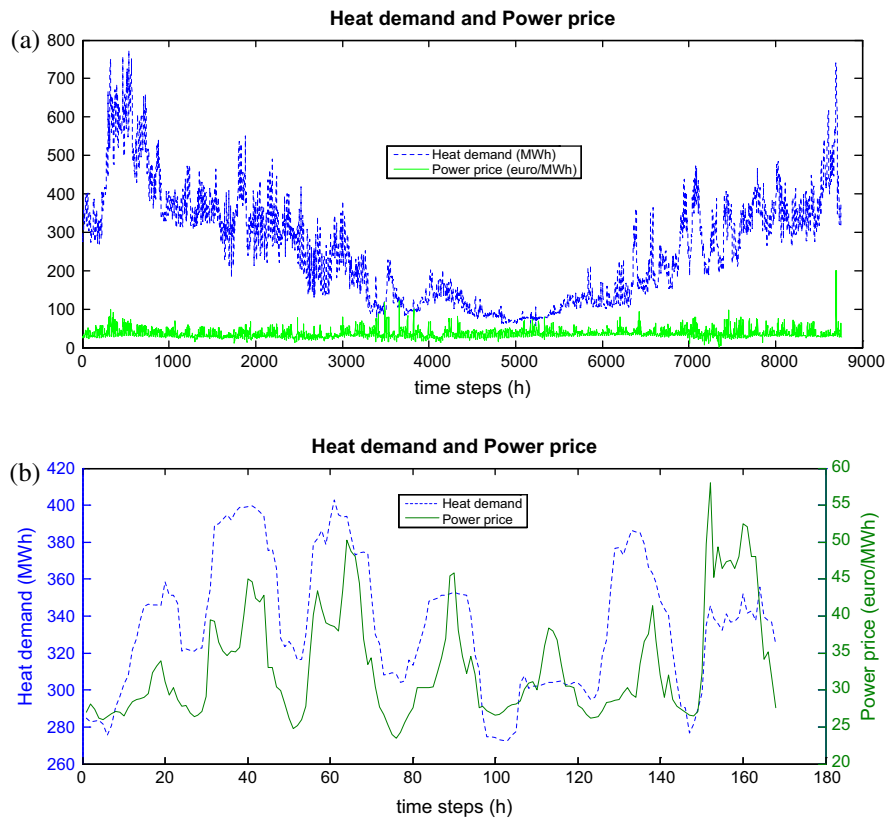


Fig. 4. Heat demand for Espoo and power price. (a) Year 2014 and (b) week 1, 2014.

standard error for the Wiener process is  $\sigma$ , then the error after  $N$  hours is  $\sqrt{N}\sigma$ . Based on the error for a 5-day forecast provided by the Finnish meteorological institute [29] we have assessed the hourly standard error for the temperature forecast  $\sigma = 0.3414$  °C. For power price, a recent study by Voronin et al. [30] presented accurate forecasting methods based on combined and decomposed data for the power market. It reported that the hourly standard error for power price can be  $\sigma = 0.2215$  €. Fig. 3 illustrates actual power sales price and simulated 5-day forecasts starting from the first and second day using exaggerated value for the standard error.

#### 2.4. Evaluation and validation of the method

To assess the efficiency of the solution method, we compare it with the *no-storage case*. The no-storage case is computed by the same CHP planning model by setting storage size to be zero. Due to the lack of storage, the no-storage case does not contain dynamic dependency between hourly CHP models. Therefore, the individual hourly models can be solved separately or in arbitrary length of chunks. As a second reference, we also compute the *theoretical optimum* based on perfectly accurate heat demand and price forecasts, i.e. actual historical heat demand and price data. To make the three cases comparable, we make the storage empty at the beginning and the end of the time horizon in each model.

The hourly CHP system model was validated by comparing the results with real-life data. Because the storage does not yet exist, validation of the sliding time window method was done by comparing the results with the no-storage case and the theoretical optimum. The sliding time window algorithm should give a better solution than the no-storage case, but not quite as good as the theoretical optimum, which cannot be reached in practice. With storage size 0 the three models should produce the same results. We consider the results for a one year time horizon for all 3 cases.

Table 2 summarizes the input data in terms of the CHP models using different time horizons.

### 3. Computational results

Because the forecasts are simulated by random processes, every run will produce slightly different results and objective function value for the sliding time window method. To eliminate the randomness and to show the availability of the model for arbitrary time horizon, we first run the model for one year. Fig. 4 shows the input data consisting of actual hourly power price from Nord-Pool spot market [24], and also the heat demand for the city of Espoo in the entire year 2014 (Fig. 4a) and for week 1 (Fig. 4b). We observe that the peaks and valleys of the power and heat curves are to some extent coincident, but non-coincident peaks and valleys also exist. This indicates that use of storage can be

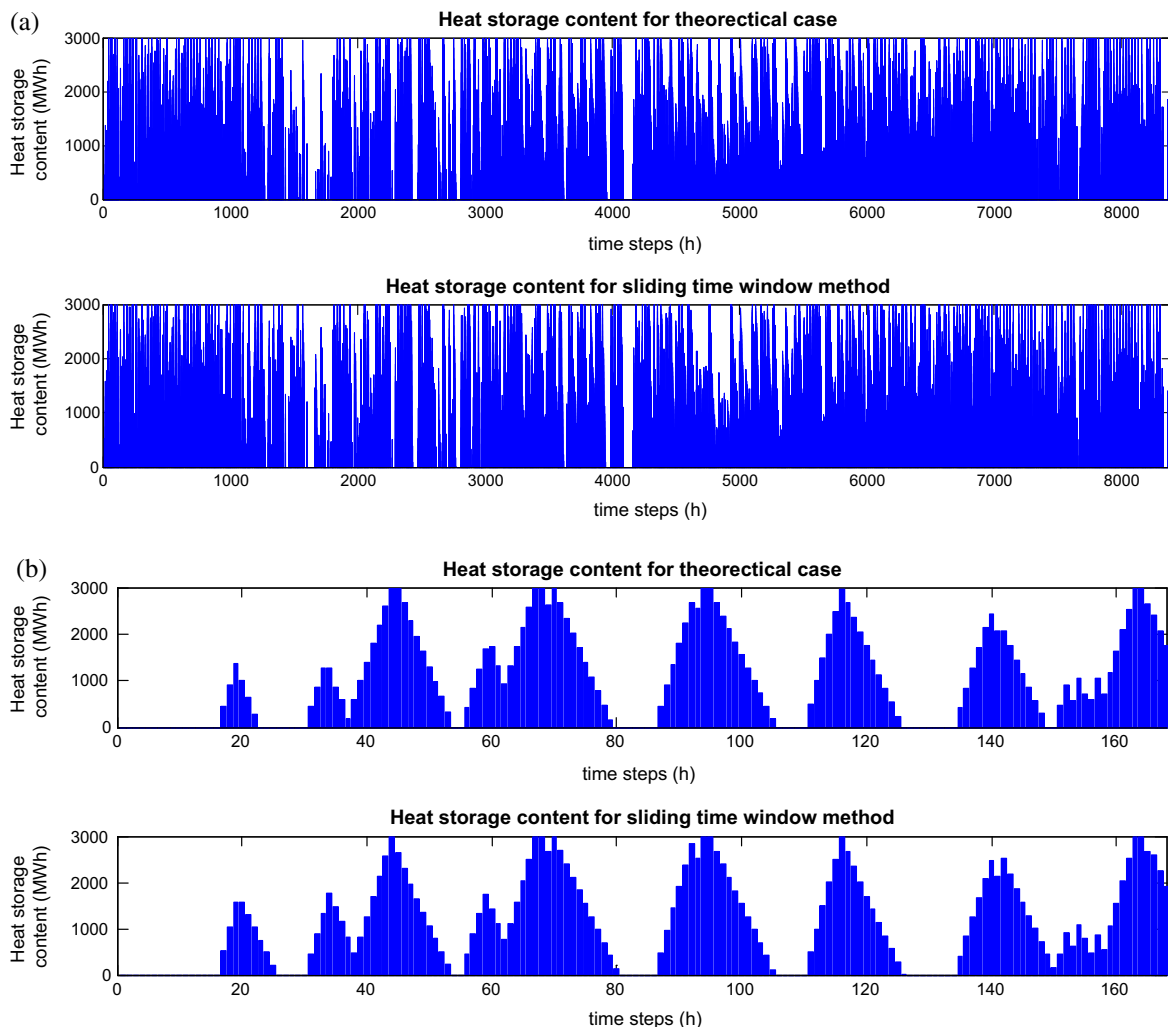


Fig. 5. Optimized heat storage level for the theoretical case and sliding time window method. (a) Year 2014 and (b) week 1, 2014.

beneficial. We input the one-year data to our model to optimize the CHP production and storage operation for the year. The figure of input data for week 1 is used to help analyze the results about the heat and power fuel consumption and heat storage content.

Fig. 5 shows the optimized heat storage level for the theoretical case and the sliding time window method. To better understand the results, we focus on week 1. We can see that both models produce quite similar plans for storage operation. The heat storage is operated aggressively between zero and its maximum capacity in order to allow producing CHP power when the power price is high, even when the heat demand is low.

Fig. 6 shows the optimized CHP fuel consumption for the theoretical case, sliding time window method and no-storage case. While the fuel price for the HOB is lower than for the CHP plant, the CHP will benefit from selling the produced power. This means that the marginal price for CHP heat depends on the variable power price.

In some hours it will be more profitable to run the CHP, other hours the HOB, and in some hours both are needed to provide enough heat.

To understand the results better, we focus on week 1; the main observation is that both the theoretical case and time window model differ dramatically from the no-storage case. The storage allows producing a large amount of heat and power during the hours when the power price is high, and satisfying the heat demand when the storage when power price is low. In the no-storage case the HOB is used significantly more and CHP is used only when power price is very high. Still, there are several hours when power price is high enough to make it profitable to operate the CHP at maximum power production while discarding excess heat. This means that without heat storage, the CHP system is operated on less-than optimal energy efficiency in order to minimize production costs. Heat storage makes it possible to simultaneously minimize costs and maximize energy efficiency.

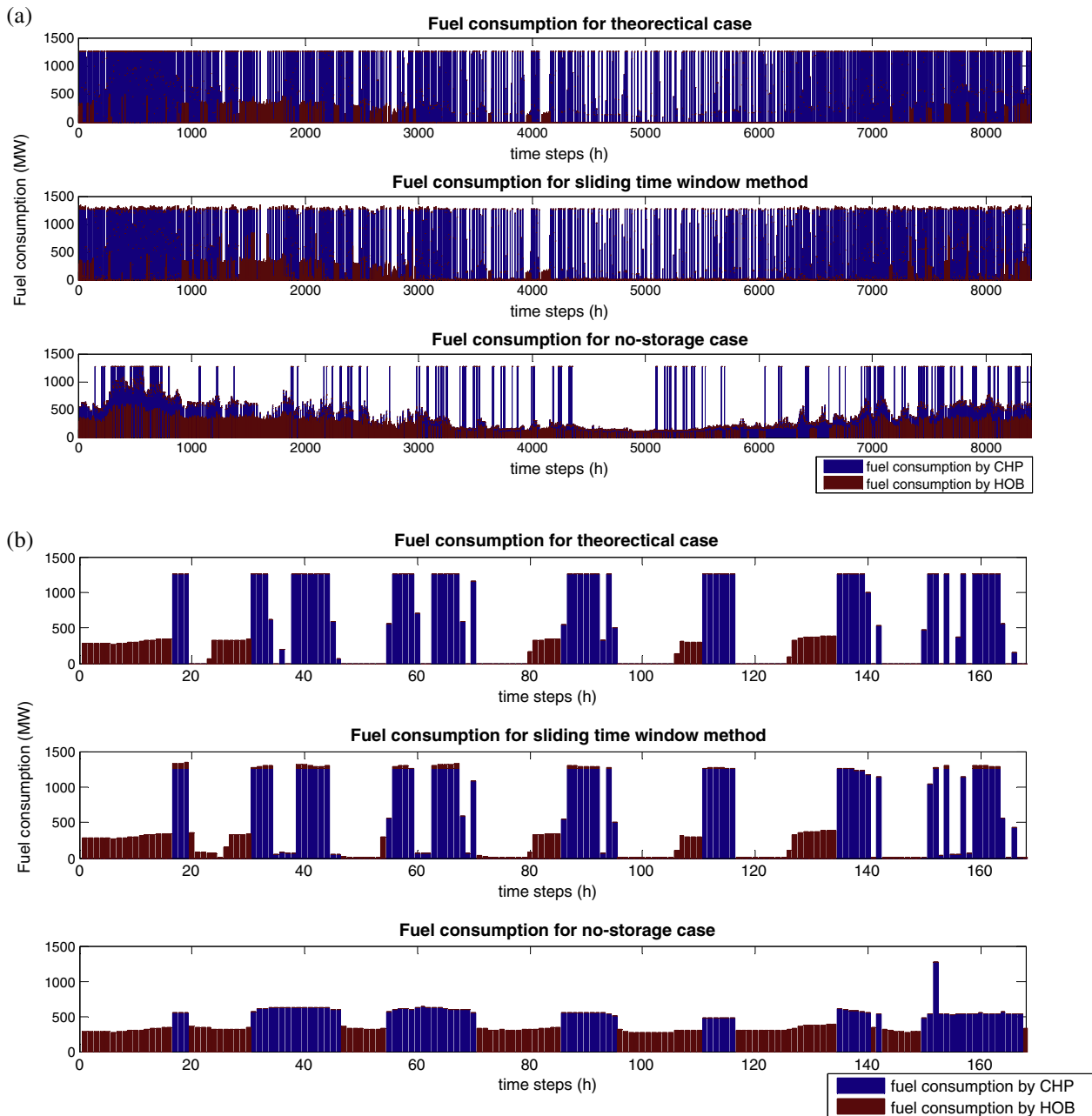


Fig. 6. Optimized fuel consumption for the theoretical case, sliding time window method and no-storage case. (a) Year 2014 and (b) week 1, 2014.

For 1-year time horizon, the objective function value (net operating costs) for the no storage case was 13.688 M€. The sliding time window algorithm produced on average net operating costs of 9.571 M€, i.e. a cost saving of 4.117 M€. In comparison, the theoretical model (which cannot be implemented in practice) yields net operating costs of 9.109 M€, i.e. cost saving of 4.579 M€. This means that considering the forecasting uncertainty, the sliding time window algorithm can obtain 90% of the theoretically possible savings derived based on perfect forecasts. This is a very good result. Also, the fact that the performance of 5-day sliding time window method is better than no-storage case and 90% as good as the theoretical case validates the sliding time window method.

#### 4. The effect of width of the time window and the storage size on the optimal cost

In the following we first analyze how the width of the time window affects the optimal cost obtained by the sliding time window method. This analysis justifies why 5-day width is chosen for the time window. Then we analyze the CHP system with different sized storages for both sliding time window method and theoretical case.

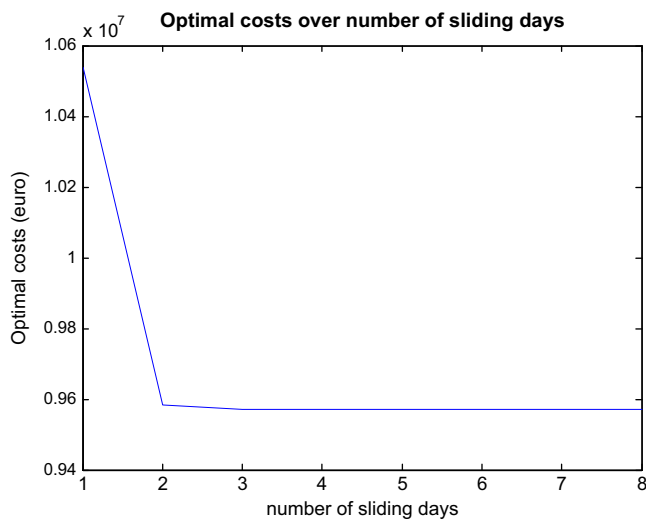


Fig. 7. The optimal net operating costs for 1 year as a function of the width of the time window.

#### 4.1. The optimal net operating cost as a function of the width of the sliding time window

The width of the sliding time window is the number of the days we look ahead each time we slide the time window. The idea of applying the sliding time window algorithm is to gain vision for the future, past the current day. We have applied the method using a 5-day time window, because the weather forecast for 5 days is considered relatively accurate, and is commonly used by energy companies in their production planning. However, even longer forecasts are available. To search the optimal width of the time window from the techno-economic point of view, we re-analyze the yearly model with different widths of the time window varying from 1 to 8 days. Fig. 7 shows the optimal net operating cost as a function of the width of the time window. We can see that the optimal operating cost drops significantly when moving from a 1-day window to a 2-day window, 1-day time window yields approximately 10.52 M€ cost then drops to 9.58 M€ for the 2-day window, but is rather flat after that. The 3-day window yields still a little better value, but after that the objective does not improve much. These results apply for short-term storages, such as the 3000 MW h storage used in the test runs. This storage size corresponds to about 8 h demand in the winter and 1.5 days in the summer. With larger storages, the optimal time window size is larger. Considering the availability and the accuracy of the weather forecasts, a 5-day time window is a reasonable choice in a short-term storage planning problem.

#### 4.2. The optimal net operating cost as a function of the storage size

In the following we run the model with variable sizes of the storage for one year. We let the storage size vary from 0 up to 10,000 MW h. The upper limit corresponds to a storage size of about 1.5 days heat demand in the winter or about 4 days in the summer. Fig. 8 shows the optimal net operating costs as a function of the heat storage size both for the theoretical case and the sliding time window method. We can see that for both cases the optimal net operating costs monotonically decreases as the storage size increases, as expected. However, the marginal benefit of increasing the storage size approaches zero. The net operating costs obtained by the sliding time window method are consistently a little larger than for the theoretical case, but very close to the theoretical case. This is natural, because the theoretical case assumes perfectly accurate forecasts which are not in practice available. These results validate that the sliding time window method is able to consistently produce storage operation plans that are nearly as good as the theoretical optimum.

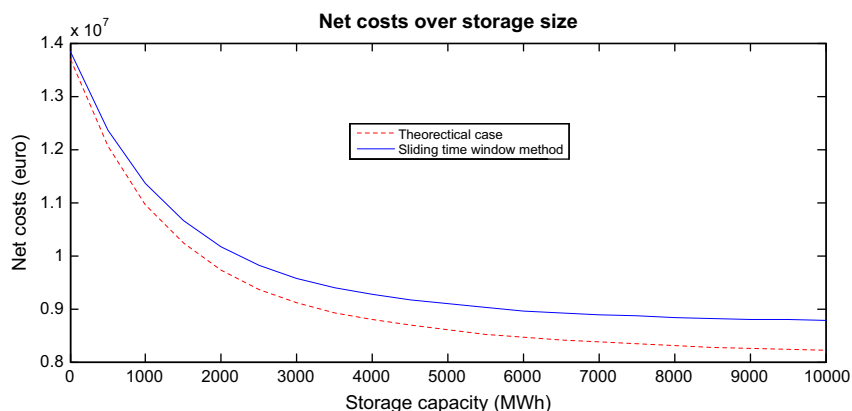


Fig. 8. The optimal net operating costs as a function of heat storage size.



When using the sliding time window method for planning the optimal storage size in a real life case, it is necessary to consider in addition to the production costs, also the investment costs. The investment costs can be made comparable with annual operating costs e.g. by the annuity method with a given interest rate and life time for the storage. The optimal storage size is at the minimum point of the total cost function. Such analysis is out of the scope of this study.

## 5. The effect of the storage size on the overall energy efficiency

To study how the storage size affects the overall energy efficiency for different models, we calculate the energy efficiency as a function of storage size varying from 0 to 10 000 MW h for theoretical case, 5-day sliding time window method and no-storage case respectively for one year. Fig. 9 shows the efficiency curves for these three cases of cost-optimal operation. For both theoretical case and sliding time window method, the energy efficiency first increases rapidly from 86% to above 90%. For the theoretical case the highest energy efficiency is at storage size 8000 MW h, while for sliding time window method 6000 MW h storage size yields maximal efficiency. This means that the theoretical case overestimates the benefit from heat storage, giving too optimistic estimates for the energy efficiency and optimal net operating costs.

Observe that the cost-optimal operation of a CHP system does not necessarily maximize the energy efficiency. To maximize energy efficiency, it is possible to modify the objective function of the model (2)–(6) to minimize the fuel consumption instead of net operating costs.

## 6. Discussions and conclusions

We have introduced the sliding time window method for planning CHP production and heat storage operation. We have demonstrated the method using heat demand data for the city of Espoo and power price information from NordPool. The method is designed to use uncertain forecasts for heat demand and power price. In the test runs, using a 5-day time window, our method obtained 90% of the theoretically possible savings that can be derived based on perfect forecasts. However, the savings depend on how non-coincident the heat demand and power price curves are, and also on the accuracy of the forecasts. In this study the forecasts were simulated by disturbing actual data by the Wiener process. When applying the method in real life, real forecasts should be applied.

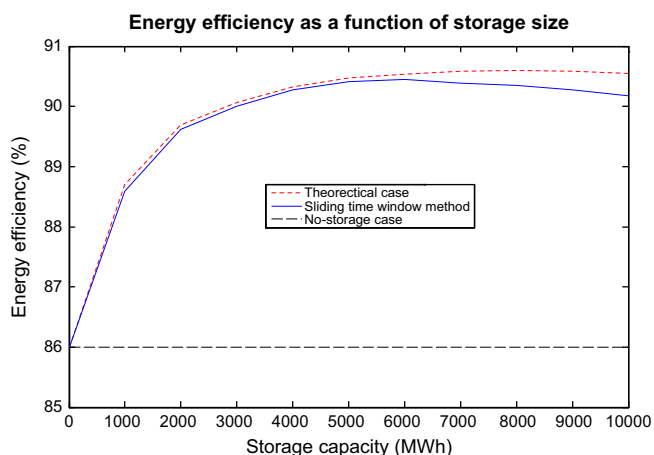


Fig. 9. The overall energy efficiency as a function of heat storage size.

Optimization results show that heat storage can significantly improve the cost-efficiency of a back pressure CHP plant, because it improves the flexibility of the CHP system; the storage allows producing CHP power when power price is high and satisfying heat demand from storage when power price is low.

The sliding time window method benefits both design and operation of the CHP systems. For system operation, it can be used operatively by a CHP company to determine how to run their production and how to operate their storage. For system design, the method can be used to help real life investment planning in order to determine if the heat storage is profitable and what the ideal size would be. In such an analysis, it is necessary to consider, in addition to operating costs, the investment costs for the storage. A larger storage results in larger savings in operating costs but also larger investment costs. The optimal storage size corresponds to the minimum of the total costs.

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