Modeling Combined Heat and Power Plants as Flex-offers

Master Thesis

Philipp Daniel Freiberger

Aalborg University
Department of Computer Science
Selma Lagerløfs Vej 300
9220 Aalborg Øst, DK

Declaration

I hereby declare that I wrote this thesis on my own and followed the principles of scientific integrity

Aalborg University, September 26, 2017

Philipp Daniel Freiberger
pfreib15@student.aau.dk

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Philipp Daniel Freiberger
Department of Computer Science
Aalborg University
Selma Lagerlfs Vej 300
9220 Aalborg st, DK
Email: pfreib15@student.aau.dk

Abstract

Increasing inflexible electricity from volatile renewable energy sources (RES) poses new challenges to fast dispatchable energy sources to balance the market. Combined heat and power (CHP) plants are highly efficient and considerably fast dispatchable. This work looks into flexibilizing the production of electricity using flex-offers. CHP operators make production bids for the day ahead market which have a fixed length and production capacity. These bids are static and this work extents the flexoffer concept by a duration flexibility to cover CHP plants.
An experimental evaluation has shown that there is an opportunity to trade with flexi orders.

1. Introduction

Traditionally, the generation of electricity followed the demand of all parties connected to the grid[29]. This was possible due to flexible power sources mainly based on fossil fuels. In the past decades, however, there has been an increasing investment in volatile renewable energy sources (RESs) like wind turbines and photovoltaic systems (PV). As a result, the generation of electricity is becoming more and more inflexible due to the dependency on uncontrollable weather situations.
The trend towards more inflexible power generators presents new challenges for fast dispatchable production to keep energy demands satisfied. In order to keep the grid stable and to avoid outages, the production and consumption of energy needs to be balanced at all times. Imbalances in the grid could lead to blackouts due to congestion. The potential effects of flexible electricity consumption and production on the stability of the power grid have already been widely investigated. Starting with an explicit modelling of the flexibility of power consumers and producers[2], the creation of an electricity market framework for flexibility[11] and analysis of the social constraints of everyday life electricity usage[30].
Flexible power generators are necessary to supplement the power production in periods of low supply from inflexible RESs to make up for shortage in the grid.

Combined heat and power plants (CHPs) are one type of flexible production units and are a potential solution to balance the energy production[25]. CHPs are power plants which usually use an engine (e.g. gas combustion) to power an alternator for electricity production while recovering thermal energy from the excess heat. The energy efficiency of modern CHPs is higher than traditional power plants which only produce electricity[25] which makes CHPs popular power generators, e.g. in Denmark and the United Kingdom[16]. Due to their high energy efficiency, the European Union is promoting CHPs to become more independent from external power sources and to reduce emission of greenhouse gases[3]. Figure 1 shows a schematic structure of a CHP. Here, a gas engine is powering an alternator to generate electrical energy. Heat exchangers convert the excess heat from the engine and the exhaustion gases to hot water, e.g. to be used for district heating. Apart from an engine to co-generate heat and electricity, CHPs often also have a boiler (electric or gas powered) which can be used to generate heat energy only. The boilers are used when it is not economical to run the engine, for example because of low electricity prices.

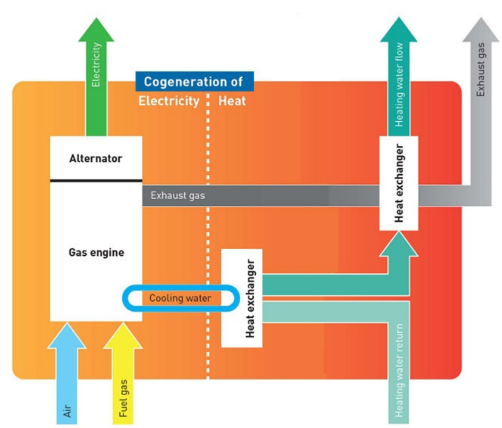

Figure 1. Schematics of a common CHP using a gas turbine. Source: https://www.mwm.net/mwm-chp-gas-engines-gensets-cogeneration/mwm-competencies/cogeneration-trigeneration-plants/

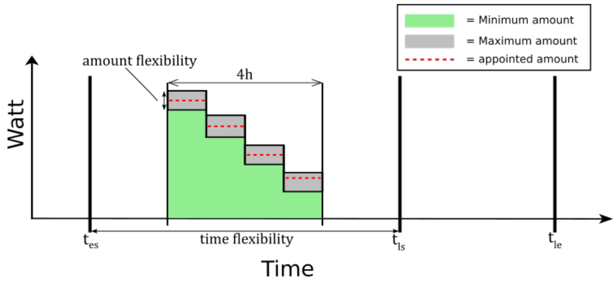

Figure 2. Basic flexoffer with time and amount flexibility

Depending on the type of technology used to generate power, the start-up time of the engine can vary a lot[25], from a couple of minutes up to over one hour. Thus, the scheduling of the power plants is vital in order to satisfy the market needs. High start-up costs can make it infeasible to run a CHP for only a short period of time.

CHPs generate heat and electricity in a cogeneration process, meaning that there is a requirement to fulfill on both ends, the electricity demand and the heat demand. Many CHPs also have thermal storage units attached to the plant. This allows a timely decoupling of electricity and heat supply, i.e. it is possible to generate electricity and store the cogenerated heat for later usage. The amount of flexibility gained by storage and delayed deployment is constrained by the storage capacity of the unit.

In this work we make an attempt to model the flexibility of CHPs by using and extending the flex-offer concept of Boehm, Dannecker, and Doms[2]. A flex-offer in its most basic form covers time and amount flexibility. Time flexibility is the possibility to shift the flex-offer within a predefined time interval and amount flexibility describes the variable amount that could be consumed or produced by the flex-offer. In addition, we extend the flex-offer concept with a duration flexibility The duration flexibility defines the possibility to keep the flex-offer activated for a longer or short time period. A common use case for a flex-offer is modeling the consumption and production of electricity by so-called prosumers. A prosumer is a party which is both able to consume and supply electricity. This could be for example household with an electric vehicle (EV) or a photovoltaic cell.

Example 1. The owner of a dishwasher wants to run the dishwasher after 21:00 and wants to have the dishes cleaned on the following morning at 6:00. The dishwasher takes 2 hours to run and requires $4kWh_e$. Ergo, the dishwasher can start running between 21:00 and 4:00.

Figure 2 shows an example of a basic flex-offer. It could for example represent the charging of an EV. The battery takes 4 hours to be charged between 80% and 100% depending on the amount charged at each time slice.

CHPs are heavily restricted when it comes to time and amount flexibility. Due to the start-up delay, it is more cost effective to run an engine for several consecutive time slices. Furthermore, gas fired engines perform more fuel efficient when running on full load[19, 12]. The engines observed in this work are all gas fired engines restricted to run on full load only[26]. For CHPs with only one engine, this means there is no amount flexibility. For CHPs with more engines, each engine can be modeled as its own flex-offer and can be scheduled separately by adhering to the common constraint of the thermal storage unit.

Example 2. A CHP operator has an engine with a capacity of 2.5 MW_e. Based on the heat consumption forecast the engine should run between 3 to 5 hours, providing either 7.5, 10 or 12.5 MWh_e electrical energy. Based on the storage capacity and the current charge of the thermal storage the engine can run between 5:00 an 13:00. Thus the engine starts producing energy earliest at 5:00 and latest at 8:00, 9:00 or 10:00, respectively, according to the assigned duration.

In periods of high wind, that is high supply from wind turbines, or periods of low consumption, the prices for electricity may drop and it can become uneconomical for a CHP operator to run the engines, as low prices for electricity can not cover the cost to produce electricity and heat from the engine. In this case, the CHP operators use only the boilers in order to provide thermal energy.

To determine whether an engine should run or not, the CHP operator makes production bids to a balance responsible party (BRP) for fixed specified intervals one day in advance. The price for a bid is chosen by the operator in a way that running the engine would be more profitable than producing the heat by other means, e.g. boilers or heat pumps[28]. When the offered prices of the bids are too high, they will get rejected. Traditionally, bids are made in so-called block orders. Block orders are specified by an amount, a start and end time, and a price. In 2016, a new type of order was introduced to the day-ahead market of Nord Pool, the flexi order. Flexi orders are similar to block orders with the difference that it is possible to specify an flexibility interval by specifying an earliest and latest start time. An algorithm then determines the starting time automatically by choosing the time which provides the best social welfare. Usually these are the times with the highest prices[27]. Introducing explicit time flexibility to the runtime of a CHP could lead to an increase in profits and help balance the electrical grid.

This work focuses on CHPs with one or more gas combustion engines, electric or gas powered boilers and a thermal storage unit. The contributions of this paper are

1) the modeling CHPs with thermal storage units as flexoffers,
2) the evaluation of benefits of flexibilizing production bids from CHP operators,
3) analyzing the the benefits of generating flexi orders instead of block orders.

The remainder of the thesis is structured as follows. Section refsec:background provides a brief overview of the current electricity market. Section 3 covers related work. Section 4 formally defines models to use describe the operation of a CHP plant as a flex-offer, and in Section 5 we evaluate the performance of the models and discuss the findings. Finally, Section 6 concludes the thesis and discusses future work.

2. Background

In this section, we give a brief introduction of energy markets, the participating parties, and of the different trading strategies within different time frames. The focus lies mainly on renewable energy sources (RES) such as wind and solar energy. However, this introduction is not intended as a complete overview of energy markets and only covers the aspects that are most relevant to this work.

2.1. Liberalization of the European Power Markets

The European Commission argues that for more secure, reliable and cost-effective supplies of energy throughout the European Union (EU), it is important that there are integrated EU energy markets[4]. Having open borders to transport energy across country borders opens the markets to competition and increases effectivity of the markets. Legislation and rules from the EU provide a guarantee for fair trading on wholesale markets and prevent manipulation of prices.
The liberalization of the energy markets within the EU began in 1996 with Directive 96/92/EC[1] which has been replaced in 2003 by Directive 200354EC[2][22]. The directive regulates market opening, third party access, and the system operators. This liberalization ended the earlier manifested local monopolies of energy providers, by reducing obstacles for competitors to enter the market. Opening markets increased the competitiveness and the size of the markets themselves. It is a part of successful liberalization of the markets, that they are well-functioning. That is, the services provided by the various parties need to make energy supply as reliable as possible[22]. Furthermore, open markets encourage participating parties to invest in Research and Development, capital formation, and more usage awareness of the energy by consumers[5].

2.2. Danish Electricity Markets

The liberalization of the Danish Power market was established in 1996 and took effect in 1998 [14]. Denmark is divided into two balancing or bidding areas: (1) DK-West (also DK1), covering roughly Jutland and Funen, and (2) DK-East (also DK2), covering mainly Zealand and Lolland. In 1999 DK1 and later in 2000 DK2 joined the common Nordic electricity market Nord Pool.
The commodities traded on the energy markets are MWhs of Energy at a given time slot. Nord Pool is the joint electricity market of the Nordic and Baltic countries. Nord Pool allows trade on two different markets: (1) the day-ahead market (Elspot) and (2) the intraday market (Elbas). In the Nordic countries, the electricity is traded on hourly intervals[36]. Additionally, for trades more than one day ahead there is the forward or futures market (FM). In the FM, the time frame for trading is usually between one week and one year, though it can differ under some circumstances [5].

1. Directive 96/92/EC aimed at big energy consumers making it possible to negotiate the purchase and sale of energy.

2. Directive 2003/54/EC opened the markets to non-household (2004) and later all consumers (2007).

The Day Ahead Market. On the day-ahead or spot market (DAH), participants place production and consumption bids one day before delivery. The DAH closes at 12:00 CET/CEST the day before delivery, meaning that all participants have to have given their production and consumption bids before that. All bids are processed by the trading system which will return the clearing price for each hour of the following day. Simplified, these prices are chosen so that there is a balance between consumption and supply of electricity. Trade bids, which are below the hourly price, are then getting settled. The physical delivery of the electricity then begins the following day from 0:00 CET/CEST onwards.
Most of the Energy on Nord Pool is traded on the DAH. In 2016, the total traded volume by the 380 participants, such as power plant operators, industrial consumers and distributors, were 391 TWh_e in the Nordic and Baltic countries[23].

The Intraday Market. The intraday market is the market for trades on the day of delivery. In Nord Pool, electricity can be traded up to one hour before physical delivery[24]. Imbalances that occur due to unforeseen incidents, like a power plant outage or inaccurate wind power forecasts, can be evened out through trade on this market, so that there is less need for regulating interference by the transmission system operator (TSO)[].In 2016 the traded volume in the whole area of the Nord Pool intraday market were 5 TWh_e[23].

2.3. Participants in the market

In the following subsections, there are brief introductions to some participants of the Electricity Market.

Transmission System Operator. The transmission system operator (TSO) is a regional/national regulation entity to oversee the energy market. The TSOs are ultimately responsible to maintain the balance between supply and consumption of energy, and to supervise the availability of a reliable energy supply[22, 36]. Due to high investment costs, the TSO holds a natural monopoly and is responsible to provide equal access to the grid to all other parties involved in the market[5].
In Europe, the grid operates on an alternating current frequency of 50 Hertz and the TSO is responsible to keep the frequency stable at all times. The TSO has different

regulatory reserves which are activate to balance the demand and supply at real time.

In Denmark the position of TSO is held by Energinet which is owned by the Danish Ministry of Climate and Energy.

Balance Responsible Party. A balance responsible party (BRP) is an institution which actively participates in the energy markets through trading. Production, consumption and trade activities are assigned to BRPs. BRPs can have a multitude of customers, e.g. power plants or industrial customers. A BRP has the financial responsibility for imbalances in the energy markets which they might cause[9, 8]. This means, if a BRP fails to balance their portfolio, they are held financially responsible and are penalized by a regulation price[36].
On the DAH, a BRP has to have a balanced portfolio, whereas on the intraday market, it is possible to take imbalances. Imbalances are taken in anticipation of deviations in production or consumption of energy, e.g. through inaccurate wind power forecasts. Imbalances, which help the system, can benefit the BRP and generate profit.
The BRP takes the role of a middle man for

3. Related Work

This section is dedicated to related work in the domains of smart grids, demand response, flex-offers, and modelling of CHPs.

3.1. Smart Grid

Research on smart grids has the purpose of optimizing the usage of power generation and consumption supported by ICT. The main goal is to optimize the energy usage from RESs [10].
The MIRABEL [2] and TotalFlex[33] smart grid projects, are two recent projects which explore flexibility in the electricity market. In the MIRABEL project flex-offers were invented as a way to model the inherent flexibility given by the domain. These projects have the goal to increase the share of energy from RESs in the total energy production.

3.2. Demand Side Management

Demand Side Management (DSM) refers to the active management of the consumption of energy. It covers energy efficiency, demand response, and dynamic demand. The energy efficiency works with the reduction of the energy usage, e.g. through improved technology[1]. The energy efficiency is also picked up with the CHP technology which convert, in our case, energy from gas into electricity and thermal energy.
Demand response (DR) describes the action to adapt the demand of energy according to the market situation, e.g. energy availability or energy prices. Consumption can be shifted to hours of less overall consumption or higher energy availability from RESs. Another possibility is on-site power generation, which would result in a demand reduction on the grid. There are two main classifications for DR: (1) incentive based programs (IBP) and (2) price based programs (PBP)[1].
Higher energy efficiency and demand response mechanisms provide a possibility to increase the share of energy from RESs which leads to environmental benefits[13].

3.3. Flexibility in Energy Demand and Supply

The volatile nature of RES suggests an increase of flexible on-demand energy sources to balance the fluctuations[25]. There is a high flexibility in the energy demand of private households[15] which can be used to establish DR system. This could help a higher usage of energy from RES.
Energy storage in general can enable a higher share of RES. Being able to shift the load by only a few hours can reduce the curtailment of RES significantly. This suggests that the advancement of storing technologies is a key point to increase flexibility in the power system on the supply side[6].
Furthermore, in order to successfully integrate variable generation, there is a need for a well interconnected power system with a low start up and ramp up time[20].

3.4. Flex-offers

In a smart grid scenario like the MIRABEL project, the number of flex-offers is huge and will increase more in the future. Thus, this renders the optimal scheduling infeasible to compute with regular hardware. In addition, there is a lower limit for the minimal capacity being able to be traded at each hour. In this subsection, there will be an overview of state-of-the-art approaches for aggregating, scheduling, and disaggregating flex-offers. In general, the goal, when aggregating flex-offers, is to retain as much flexibility as possible and to schedule the flex-offers to use energy optimally from RES under constraints. Flex-offers cover both sides, DR and CR, as they can be modeled to represent demand and supply of Energy.

Aggregation and Disaggregation. There has been introduced several techniques to aggregate and disaggregate flex-offers in order to reduce the amount of variables within the scheduling problem. When aggregating flex-offers, there are three conflicting requirements which one has to consider: *Compression*, *Flexibility* and *Efficiency*. In [32], the authors introduced the *start alignment* (SA) aggregation based on time and amount flexibilities which aggregates flex-offers with similar flexibility properties. The aggregation is split in two stages, *(*grouping) and *bin-packing*. In the grouping stage, similar flex-offers are grouped based on similarity thresholds. In the bin-backing stage, constraints are applied to the groups, e.g. no more than 10 flex-offers in one bin. The second stage is important to retain as much flexibility as possible. If for example hundreds of flex-offers have the same properties, it would not be possible to schedule them at different times anymore. More recent approaches include grid constraints when scheduling and (dis-)aggregating flex-offers. The constraint specifies a minimum and maximum capacity for the grid which should not be violated at any given point of time[35, 34]. Two algorithms were introduced, an *simple greedy* (SG) and an *exhaustive greedy* (EG). Dependency-based flex-offers expand the regular flex-offer concept by adding dependency properties between time-slices[31]. This means that the amount of energy consumed in later timeslices is dependent on the scheduled amount in preceding time slices. This could for example be heat pumps which can have different production patterns giving comfort levels of the user, or an EV which can charge at an higher rate in the beginning and a lower rate in the end compared to a regular charging rate.

Scheduling. The scheduling of flex-offers is independent from the sort of flex-offers it is presented with, i.e. whether they are aggregated or not. The raw scheduling problem is a linear programming problem which tries to minimize the imbalance between supply and demand of energy. This could for example mean to schedule the consumption flex-offers at times of high winds so there is a lot of energy produced by wind turbines. In [2] and [7], there are two algorithms introduced for scheduling a *randomized greedy search* (GS) and an *evolutionary algorithm* (EA).

3.5. Modelling of CHP plants

Several case studies have investigated the optimal operation of a CHP over the course of a year. Evidence has shown that the attachment of a thermal energy unit increases the efficiency and profitability of the CHP operation. The three strategies to run a CHP are (1) heat demand driven, (2) electricity demand driven or (3) a combination of (1) and (2). A combined heat and electricity led strategy has shown to be most cost effective during winter months[17].
The effects of heat storage to the optimal power generation plans of CHP plants have been investigated. Also, the influence of operating a CHP with a thermal storage has been widely investigated. The addition of a storage unit to a CHP has shown to be increasing the profitability on the German spot market [21] and the return of investment of a plant in the United Kingdom has shown to highly increase with a storage unit attached[12].
Hellmers et al.[18] modeled a combined portfolio a CHP and a wind turbine park. They have shown that there is a good possibility for CHP plants to keep the balance in the portfolio to reduce penalties through imbalance. The focus here is on a portfolio optimization for plants under the same operator instead of a portfolio handled by a BRP..

4. Model

In this section, it is explained in detail how the flex-offer concept can be used to model the production of CHPs. First, we formally define flex-offers and how we are going to extend them. Secondly, we describe how to model the operation of a CHP. Finally, we define how the CHP model can be translated into flex-offers. We focus on CHP plants with one gas engine, a gas boiler and a thermal storage unit. The gas engines are operated as running always on full load. This means the CHPs modeled in this work have a fixed output. In Table 1, there are descriptions of all variables introduced throughout the paper.

TABLE 1. DESCRIPTION OF ALL UNITS

Variable	Description	Unit
C	CHP	-
e	Engine	-
e^c	the electricity capacity of the engine	kW
$e^{wu/cd}$	warm up and cool down time	seconds
$e^{ru/rd}$	ramp up and ramp down time	seconds
e^{su}	total start up times $e_{wu} + e_{ru}$	$seconds$
e^{st}	total stop time $e_{rd} + e_{cd}$	$seconds$
$e^{eff,g}$	total energy efficiency factor of the engine	-
$e^{eff,p}$	power efficiency factor of engine	-
$e^{eff,h}$	heat efficiency factor of engine	-
e^h	the the heat capacity of the engine	kW_{th}
e^{uc}	the energy produced during ramp up	kWh_e
e^{dc}	the energy produced during ramp down	kWh_e
e	the energy produced during ramp down	kWh_e
b	Boiler	-
b^c	maximum heat production capacity	-
b_t^h	heat produced by boiler at time t	-
$b^{eff,h}$	heat efficiency factor of engine	-
s	the storage unit attached to CHP	-
s_t^l	the filling of the storage at time t	kWh_{th}
$s^{min/max}$	the upper and lower boundary the filling s_l has to be within these boundaries	kWh_{th}
s^{in}	maximum feed in rate of the storage unit	kW_{th}
s^{out}	maximum feed out rate of the storage unit	kW_{th}
hd_t	heat demand in hour t	kWh_{th}
hp_t	heat produced by CHP in hour t	kWh_{th}
F	set of all feasible flex offers	-
f	flex-offer	-
p^e	electrical energy production profile	-
p^h	thermal energy production profile	-
t^{es}	earliest start time of flex-offer	-
t^{ls}	latest start time of flex-offer	-
$r^{(i)}$	timeslice of flex-offer	-
a^{min}	minimum amount of a slice $r^{(i)}$	-
a^{max}	maximum amount of a slice $r^{(i)}$	-
d^{min}	minimum duration of flex-offer	-
d^{max}	maximum duration of flex-offer	-
$p_{dur}(f)$	duration of flex-offer f	-
f^{max}	flex-offer which maximizes the profit	-
λ_t^s	estimated spot price electricity at time t	€$/MWh_e$
λ^h	estimated price for thermal energy	€$/MWh_{th}$
μ_t^g	gas price at time t	€$/MWh_g$
μ^{oe}	operation and maintenance cost of the engine	€$/MWh_e$
μ^{ob}	operation and maintenance cost of the boiler	€$/MWh_{th}$

TABLE 2. RUNNING EXAMPLE

Variable	Value
e^c	2500 kW
e^{ru} & e^{rd}	240 sec
e^{wu}	360 sec
e^{cd}	150 sec
$e^{eff,g}$	0.95
$e^{eff,p}$	0.37

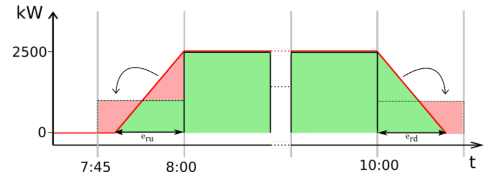

Figure 3. Start up time for a CHP

4.1. Flexoffer

A basic flex-offer is defined in [32] as follows

Definition 4.1. Basic Flex-offer [Defintion 1 in [32]] A flex-offer f is a tuple $f = ([t^{es}, t^{ls}], p)$ where $[t^{es}, t^{ls}]$ is the start time flexibility interval, and p is the amount profile. The time is discretized into equal-sized units, e.g., 15 minute intervals. Thus, we use $t_{es} \in N$ to specify the earliest start time and $t_l s \in N$ to specify the latest start time. The p is a sequence of slices $< r^{(1)}, \ldots, r^{(m)} >$, where a slice $r^{(i)}$ is a continuous range $[a^{min}, a^{max}]$ defined by a minimum amount a^{min} and a maximum amount a^{max}. The extent of $r^{(i)}$ in the time dimension is 1 unit. Hence, a flex-offers profile duration is computed as $p_{dur}(f) = |f.p|$, its earliest end time as $t^{ee}(f) = f.t^{es} + p_{dur}(f)$, and its latest end time as $t^{le}(f) = f.t^{ls} + p_{dur}(f)$.

This however is not sufficient to completely model the flexibility and constraints given by a CHP. We now define how we extend the basic flex-offer concept by adding another layer of flexibility, the duration flexibility.

Definition 4.2. Extended Flex-offer [Defintion 1 in [32]] An extended flex-offer f is a tuple $f = ([t_{es}, t_{ls}], p^e, p^{th})$, where $[t_{es}, t_{ls}]$ is the start time flexibility interval defined as before, p^e is the electricity amount profile, and p^{th} is the thermal amount profile. All other properties are defined as seen in Definition 4.1

In the following, f refers to an extended flex-offer unless mentioned otherwise.

Definition 4.3. Meta Flex-offer A meta flex-offer m is a sequence of extended flex-offers $< f^{(1)}, , f^{(r)} >$, where a flex-offer $f^{(i)}$ has a different duration $p_{dur}(f1^{(i)})$ within a discrete interval $[dur_{min}, dur_{max}]$, defined by minimum flexoffer duration dur_{min} and a maximum duration dur_{max}.

4.2. CHP Model

A CHP C is a tuple $C = (e, b, s)$ where e denotes a gas combustion engine, b a gas fired boiler and s a thermal storage unit.

Engine. The engine is defined by a power capacity e^c, start up and stop parameters, and efficiency factors.

Ramping. There is a warm-up time e^{wu} between sending the start signal to the engine and the engine becoming productive. In this time, the environment is setup, for example the ventilation is started[26]. Following this, the ramp-up and ramp-down times, e^{ru} and e^{rd}, respectively, are the times the engine needs to go from zero load to full load and vice versa. The cool down time e_{cd} is the time which the engine needs to fully cool down.
As an example, consider a CHP with one gas engine and the properties shown in Table 2. Then, the total start up time e^{su} is defined as the sum of warm-up and ramp-up time, $e^{su} = e^{wu} + e^{ru}$. This means it takes $360 + 240 = 600$ seconds (10 minutes) for the engine from activation to 100% load. The total stop down time on the other hand is given by $e^{st} = e^{rd} + e^{cd}$, in this case $240 + 150 = 390$ seconds.

The ramping times do in fact contribute to the total heat and electricity amount produced and therefore have to be taken into account when scheduling. The ramping rate can be assumed to be linear[26] and the amounts produced during the ramping up e_{uc} and down e_{dc} phases are defined as:

$$e^{uc} = \frac{e^{ru} \cdot e^c}{2}, \tag{1}$$

$$e^{dc} = \frac{e^{rd} \cdot e^c}{2}. \tag{2}$$

Figure 3 shows the amount produced during both ramping phases. The amount produced in these phases is getting averaged on the whole traded time interval. For example, we look at the example engine from above again. Then during ramp-up an additional $\frac{240\text{sec} \cdot 2500\text{kW}}{2} / 3600 = 83.33\text{kWh}$ of electricity is produced. The same amount is produced in this example during the ramp-down phase.

Efficiency. Furthermore, in order to describe the dependency between heat and electricity production, each engine has (1) a total efficiency factor $e_{\mathit{eff},g}$ and (2) a power efficiency factor $e_{\mathit{eff},p}$. The factor $e_{\mathit{eff},g}$ describes the conversion rate from the input commodity, here gas, to both electrical and thermal energy. The power efficiency factor describes the partial conversion rate of the input commodity to electrical power. The partial conversion rate for thermal power $e^{\mathit{eff},h}$ and the heat production e^h are then defined as follows, recall that e^c denotes the engines total electricity capacity:

$$e^{\mathit{eff},h} = e^{\mathit{eff},g} - e^{\mathit{eff},p}, \tag{3}$$

$$e^h = \frac{e_c \cdot e^{\mathit{eff},h}}{e_{\mathit{eff},p}}. \tag{4}$$

In our example, this means that the thermal efficiency factor is $e^{eff,h}$ is 0.58 and the total thermal power output of the engine is about $3919kW_{th}$ $(2500kW_e \cdot 0.58/0.37)$.

Boilers. Boilers can be either powered by electricity or gas. In contrast to the engines, the boilers only produce heat and are able to run on variable loads. A boiler b is characterized by a heat production capacity b^c and an efficiency factor $b_{eff,h}$, defining the rate at which the input commodity, i.e. gas or electricity, is converted into heat. Similar to the engines, the boilers have ramping times b^{ru} and b^{rd}. The heat produced by the boiler b at time t is defined as b_t^h with $b_t^h \in [0, b^c$

Thermal Storage. Formally, a thermal storage unit s is specified by a storage capacity s^c and a continuous filling interval $[s^{min}, s^{max}]$ that consists of a lower boundary s^{min} and an upper boundary s^{max}. The feed in and feed out capacities are s^{in} and s^{out}. The energy content of the storage at time t is defined as s_t^l: Equation 5 specifies that the load has to be within the upper and lower boundary of the storage unit.

$$s_t^l \in \left[s^{min}, s^{max}\right], \tag{5}$$

Equation 6 specifies that the produced heat cannot be higher than the maximum feed in rate and Equation 7 specifies that the demanded heat cannot be higher than the feed out rate of the storage unit at any point in time.

$$0 \leq hp_{t-j} \leq s_{in} \tag{6}$$

$$0 \leq hd_{t-j} \leq s_{out} \forall j \in \{1, 2, ..t-1\} \tag{7}$$

.

Here, the heat demand hd of CHP C is defined as a sequence $< hd_0, ..., hd_{n-1} >$ where each hd_t defines the heat demand for the following hour starting at t. Respectively, the heat production hp of CHP C is also defined as a sequence $< hp_0, ..., hp_{n-1} >$ where each hp_t defines the heat produced in the hour starting at t.

$$hp_t = b_t^h + e_t^h \tag{8}$$

with e_t^h being the amount of heat produced by the engine at time t.

4.3. Flex-offer Generation

Due to the localized nature and well defined production levels of CHPs, it is possible to optimize the usage of a CHP locally, solely based on the market price situation given in the spot price forecasts. The duration range boundaries are chosen as follows:

$$dur_{min}\{\arg\min x \exists \lambda^s : \\ 0 \leq \sum_{t=i}^{t+x} \lambda_i^s - (e^{uc} + (x-2) * e_c + e^{dc}) * \mu_t^g\} \tag{9}$$

for $i \in [0, n-x]$.

$$dur_{max} = \lceil \frac{sum_{t=0}^{n} hd_t}{heat_c apacity} \rceil \tag{10}$$

Equationr̃efeq:dmin defines that the minimum duration is the duration so that there exists a long enough consecutive time period so that the costs of running the engine is matched by the forecasted prices.
Equationr̃efeq:dmax defines that the maximum duration is exactly so long as there the complete forecasted heat demand covered.
The filling level s_t^l is defined as in Equation 14.

$$s_t^l = s_{t-1}^l + b_{t-1}^h + f_{t-1}^h - hd_{t-1} \tag{11}$$

$$s_t^l = s_{t-2}^l + b_{t-2}^h + f_{t-2}^h - hd_{t-2} + b_{t-1}^h + f_{t-1}^h - hd_{t-1} \tag{12}$$

$$\vdots \tag{13}$$

$$s_t^l = s_1^l + \sum_{j=2}^{t-1} b_j^h + f_j^h - hd_j \tag{14}$$

with s_1^l being the rest capacity from the day before. Equation 14 adheres to the constraints defined in Equations 5, 6, and 7.

$$f_i^t = \begin{cases} 0, & \text{if } t \notin \{i, i+1, ..., i+f_l\} \\ e^{uc}, & \text{if } t = i \\ e^{dc}, & \text{if } t = i + f_l \\ e^c & \text{otherwise} \end{cases} \tag{15}$$

with $t \in 1, 2, ..., n$

The earliest start time f_{es} of the flex-offer is then defined as the minimum starting time i so that the constraints 5 are satisfied. As the heat from a CHP is traded on a daily basis, the gradient of loss is negligible[26].

The cost of operating a CHP is depends on fuel costs, and costs for operation and maintenance. The costs of running the engine $c(e)$ and the the boiler $c(b)$, respectively, are defined as follows:

$$c(e) = \sum_{i=0}^{n-1} \mu_t^g \cdot e_t^{gas} + (\mu^{oe} \cdot e_t^h \tag{16}$$

where e_t^{gas} is the amount of gas used by the engine at time t

$$c(b) = \sum_{i=0}^{n-1} \mu_t^g * b_t^{gas} + \mu^{ob} * b_t^h \tag{17}$$

where b_t^{gas} is the amount of gas used by the boiler at time t
The sales of the CHP plant are defined as:

$$\text{sales} = \sum_{i=0}^{n-1} e_t^e \cdot \lambda_t^s + hd_t \cdot \lambda^h \tag{18}$$

$$\text{profit} = \text{sales} - c(a) - c(b) \tag{19}$$

Scheduling. The scheduling for a single flexoffer per time interval is defined by iterating through all flex-offers of the meta-flexoffer checking all possible combinations and choosing the flexoffer configuration which maximizes the profit.

$$maximize 19 \tag{20}$$

When we have multiple flex-offers $f^{(i)}$ there are some more constraints on the scheduling.

$$f^{(i)}_{\text{start}} + p_d ur(f^{(i)})) < f^{(i+1)}_{\text{start}} \tag{21}$$

where $f_{\text{start}} \in [f_{es}, f_{ls}]$.

For the planning of five days ahead we used a greedy algorithm with a steadily growing time frame and dynamically created flexoffers. Below,there are three algorithms in pseudo code to give a intuition on how flex-offers are generated and the optimization is done. Algorithm̃refalg:create create flex-offers based on the heat forecast and the engine and storage specifications. Algorithm 2 explains how the most profitable flex-offer configuration is found. Algorithm 3 shows how the greedy algorithm is working.

Algorithm 1: Creat flex-offers

Data: Engine e, Storage s, Heat demand hd
Result: meta-flex

dur_{min} = 3 dur_{max} = $\lceil |hd|/e^c \rceil$ $f^{max} = Null$
foreach *dur in* $[dur_{min}, dur_{max}]$ **do**
  $f.p^e = [e^{uc}, e^c * (dur-2), e^{dc}]$ $f.p^h = f.p^e \cdot eff_h/eff_p$ **foreach** $starttime in [0, len(hd) - dur)]$ **do**
    foreach *j in* $range(0, dur)$ **do**
      $S[starttime + j + 1] = s[i+j] + f.p^h[i+j] - hd_x[i+j]$
      if $s[i+1+j] > s_max$ **then**
        reject
      end
      $starttimes.add(starttime)$ $f.t_{es} = min(starttimes)$
    end
    $f.t_{ls} = max(starttimes)$
  end
  meta-flex.add(f)
end

Algorithm 2: Scheduling of flex-offers

Data: flexoffer f
Result: f^{max}

$profit_{max}$ = $-\infty$ **foreach** *starttime in [t.es, t.ls]* **do**
  cost += startupcost **if** *f overlaps with previous* **then**
    $f.p^e[0] = e^c$ $f.p^h[0] = e^h$ $cost- = startupcost$
  end
  foreach *hour in range(n)* **do**
    $heat_b = max(0, hd[hour] - (heat_e + (s[hour] - s^{min})))$ $s[hour+1] = s[hour] + (heat_e + heat_b) - hd[hour]$ **if** $s[hour+1] < s^{min}$ *or* $s[hour+1] > s^{max}$ **then**
      reject
    end
    $cost+ = c(f) + c(b)$ $sales+ = sales(f)$
  end
  profit = sales-cost **if** $profit > profit_{max}$ **then**
    $profit_{max} = totalprofit$ $f^{max} = f$
  end
end

Algorithm 3: Five day ahead scheduling

Data: engine, storage, hd, days
Result: schedule

start=0 **foreach** *day in days* **do**
  meta-flex = createflex(engine, storage, hd[start:end])
  foreach *flexoffer in meta-flex* **do**
    f^{max} = scheduler.schedule(flexoffer) Schedule.add(f^{max})
  end
end

5. Evaluation

The Evaluation covers three aspects of using flex-offers as an optimization method for the trading of CHPs. First, in Section 5.1 the experimental framework is described. In Section 5.2, covers an evaluation of the performance and flexibility of the day ahead trading with the use of flex-offers. Section 5.3 compares the trading performance of using a single flex-offer or two flex-offers to plan the production for a day. In Section 5.4, a comparison is made between a day to day planning strategy and a five day ahead trading planning strategy.

5.1. Experimental Framework

In the following two subsections, there will be a short description of the data, the software and the hardware used to conduct the experiments.

Data. In this work, we consider a total of 33 CHP plants in the balance areas DK1 (3) and DK2 (30). Each CHP is equipped with one gas combustion engine, one gas boiler and one storage unit. The power capacity of the engines range from 288 kW to 3.14 MW and the total efficiency from 83.3% to 96.85%. All experiments were conducted on three closed intervals of each five days in the late year 2016:

3-7 October, 7-11 November, and 23-27 December. These time intervals have been chosen to analyze the performance under different market circumstances and different weather conditions. Table 3 shows the operational data for the experimental simulations. The values are estimated based on the conversation with a CHP plant operator[27]. The start up cost is estimated based on previously placed bids. Due to the similar size of the observed CHP engines and boilers, the same values can be used for every plant.

TABLE 3. DATA USED FOR THE EXPERIMENTAL SIMULATIONS

	Value
O&M Gas Engine	7 Euro/MWh_e
Start Up Cost	50 Euro
O&M Gas Boiler	0.3 Euro/MWh_{th}
Price for Heat Energy	24.5 Euro/MWh_{th}
Price for Gas	daily spot price from Gaspoint Nordic
Price for Electricity	hourly spot price from Elspot

Software & Hardware. All experiments were conducted on a standard computer with an Intel i5 2.6GHz processor, 8GB RAM and a 420 GB hard disc drive. The software is implemented in Python 3.6 using the Anaconda 4.4.0 distribution and is running on Windows 10 Home. In Table 4, there is a short list of python modules used which are not part of the standard python distribution.

TABLE 4. THE VERSION OF THE NON-STANDARD PYTHON MODULES USED IN THE CODE

module	version
numpy	1.13.1
pandas	0.20.1
pymongo	3.4.0

When conducting the experiments, we assume the storage to be the storages minimum in the beginning and having a maximum rest filling of up to 0.1MWh_{th} above the storages minimum in order to get a baseline for the profit generated. When looking only on a single day, there will not be made any assumptions about following days. The problem is optimized locally. Then, based on the optimal solution, block orders are placed at cost for the optimal solution.

5.2. Day Ahead Trading with single flex-offers

In this section, we analyze the results when optimizing the heat and electricity production one day ahead, and what influence there could be if a flexi order was traded instead of a block order.

There are 495 different instances to plan a day ahead. In Table 5, there is an overview of how often the optimal solution includes the usage of the engine or only relying on the boiler, respectively. Roughly half of the time (241), the most economical variant to operate the CHP on the DAH is to use the engine to cogenerate electricity and thermal energy. The distribution over the three time periods is different for each time period. In October, the distribution is the most uniform. In November, the engine is activated in more than 95%. On the contrary, in December, the engine is only used eight times in total. The low engine usage in December can be explained through extremely low electricity prices, reaching even negative prices. This would increase the costs of running the engine instead of generating revenue.

Table 6 shows the difference between the forecasted profits and the actual profit from the production plan that was optimal according to the forecasts. On average, the actual profit is about 4 Euro lower than what was projected. There are 133 instances where the actual profit is lower, and 111 instances where the actual profit is higher than what was prognosed. The mean absolute difference between forecast and realized profit is 11.96 Euros with a standard deviation of 9.39 Euros.

Flexi Order. For this analysis, we compare the chosen configuration of the flex-offer with the possibility of placing a flexi order instead of a block order. Therefore, we look into the accepted flex-offer duration and compare how a flexible start time could affect the trading performance.

In the 244 instances where a flex-offer is accepted, the optimal start time for the chosen duration is 188 times equal and 56 times different. Table 7 shows the occurrences of the offset between the scheduled start time and the start time of the actual optimal solution based on the actual market prices. The profit, when scheduling at the start time deemed optimal by the forecasts, is about 82104 Euros. Adding flexibility of one hour before and after the scheduled time, where, possible, holds an additional benefit of 355 Euros. This is an increase of less than half a percent. Increasing the flexibility to 2 hours before and after the scheduled time yields an additional profit of 419.57 Euro. This, however, is only the case when the flexi orders are placed at the most lucrative timeslot.

In case the least lucrative time slot is chosen, under a start time flexibility of one hour before and after the scheduled time, there is a massive decrease in profit of 34583 Euro. This is an equivalent of more than 42% decrease in profit.

5.3. Day ahead trading with 2 flex-offers

Here, we compare the trading performance from planning the following days heat and electricity production with using one flex-offer for the day compared to using two flex-offers. Figure 4 shows the average hourly spot prices for the year 2016. We can clearly see that there are 2 local maxima, one in the hour after 8:00 oclock and the other around 17:00 to 19:00. This suggests that there might be a higher value achievable when splitting flex-offers up into two separate flexoffers. It also might provide the possibility to run the engine for more hours without reaching the storage maximum filling.

Of the 244 accepted flex-offers there are 184 times also accepted when scheduling with 2 flex-offers. However, in 147 times the projected profit is higher when scheduling

TABLE 5. DISTRIBUTION OF FLEXOFFER ACTIVATION AND THEIR DURATION IN EACH OF THE 3 TIME INTERVALS

Duration	**0**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
October	73	0	0	3	15	11	16	8	5	9	9	3	1	2	1	0	1	1	1	3	1	3
November	22	3	0	0	2	8	7	11	11	4	4	9	5	4	1	6	5	5	11	9	7	31
December	156	0	0	1	1	1	0	0	0	0	0	0	0	2	1	0	0	1	1	0	0	0
Total	251	3	0	4	18	20	23	19	16	13	13	12	6	8	3	6	6	7	13	12	8	34

TABLE 6. MY CAPTION

	mean	**min**	**25%**	**50%**	**75%**	**max**
forecast	340.58	41.04	143.21	233.18	412.47	2774.01
actual	336.49	35.16	140.56	226.30	410.14	2697.61
delta	-4.08	-466.63	-25.78	-2.99	22.51	192.64
percentage	-0.69	-54.04	-10.33	-1.57	9.23	68.22

TABLE 7. START TIME OFFSET BETWEEN THE SCHEDULED SOLUTION AND THE ACTUAL OPTIMAL SOLUTION

Offset	**-9**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**8**
Occurrences	1	3	1	1	10	188	25	6	4	4	1

with only one flex offer during a day. This is most likely due to the start up costs when starting the engine again. This is despite the fact that in around 65% of the cases the engine is running more hours when scheduled with two flex offers.

5.4. Longterm planning

We also compared the trading performances for the planning of one day ahead and a five days ahead planning scheme. The actual profit made varies greatly on the accuracy of the price forecasts.
A longer time horizon when scheduling yields in total around 9865 Euros more than scheduling from day to day. 66% of the long term schedules are more profitable than a day to day scheduling and the profit is on average about 100 Euro higher per 5 day period.

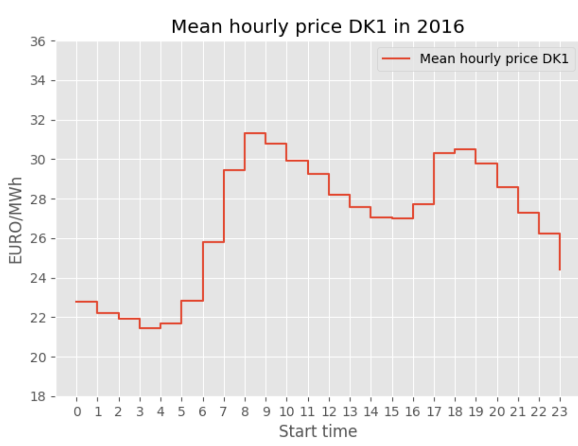

Figure 4. Mean average spot prices per MWh in DK1 in 2016

6. Conclusion and Future Work

In this section we conclude on the findings and give a brief outlook on possibilities to further use flex-offers in the electricity market.

6.1. Conclusion

We have extended the basic flex-offer concept. First, we extended the basic flexoffer by an additional amount profile in order to be able to adhere to multiple constraints. Then, we added an additional layer in form of a duration interval. By adding a duration flexibility, the possibility to perform an activity for a flexible amount of time, we are able to model dispatchable, i.e. flexible, power generators as flex-offers.
We have shown that there is a possibility for flexi orders to increase the profits generated by operating a CHP over the traditional block offer model. However, we have also shown that there could be great risks if the flexi order bid is to low. Furthermore, we have shown that in the majority of the cases a uninterrupted operation of the engine is more profitable than a simple method when splitting up the production into two flex-offers.
We have shown that flex-offers can also be used for a planning multiple day ahead. However the algorithm used has a naive greedy approach. A more adaptive algorithm might yield better results.

6.2. Future Work

In the future it would be interesting to investigate the possibility to use CHPs explicitly to balance the portfolio of a BRP in the intraday market. In times of high fluctuations of wind, a CHP flexoffer could be rescheduled or the duration could be extended or reduced to make up for changing external conditions.
This work focused only on a small subset of available CHP plants. In the future the model shown here could be extended to cover CHP plants with multiple engines. Also the CHP plants with electrical boilers could be interesting to look at, as those can both, consume and produce electricity. Many CHPs also have other heat sources like solar panels or heat pumps which would contribute to a much more complex model.
Future directions for integrating flex-offers into the trading of the market could be the modeling of cross border capacities. Cross border capacities can be used to balance a shortage in one country with the surplus of another country. In the future it might also be interesting to look into other power generators to be modeled as flex-offers.

Especially pumped-storage hydro power plants have the advantage of being able to both produce and consume energy; consuming when pumping water into the storage and producing when water is flowing through the turbines. This property is very interesting to introduce further flexibility in balancing the power market with an increasing amount of volatile producers. Under this consideration, modeling electricity production from wind turbine parks and solar plants as flex-offers is compelling.

Wind belongs to the class of volatile variable energy sources. These energy sources are inherently dependent on the current weather situation and for scheduling purposes, we rely on the accuracy of forecasts. When modeling wind production as flex-offers, the earliest start time t_{es} and the latest start time t_{ls} are set to the same time, i.e. there is no time flexibility. However, for trading purposes we can model an amount flexibility. The amount flexibility could be defined as a confidence interval around the forecast. Values above the forecasted value can be interpreted as risk values and values below it can be interpreted as safety measures.

Solar power plants also belong to the group of volatile inflexible energy sources. Here as well the production forecasts rely on weather forecasts. Especially clouds, which cover PV plants, can reduce the production by a magnitude in a short timeframe. Clouds can often appear in smaller numbers and make it hard to predict if a PV plant is (partially) covered in a given timeslot.

Acknowledgments

The author would like to thank NEAS Energy A/S for providing valuable insights and data for experiments.

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