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Waste heat from data centers: An investment analysis

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ABSTRACT

The growth of computing and Internet use have attracted the attention of the general public concerning the carbon footprint of data centers (DCs). Previous research has focused on the implementations of energy efficiency activities. However, little research has been published on the economic evaluation of waste heat utilization in the DC industry. This paper aims to provide an economic investment assessment of DC waste heat utilization. The contribution of this paper is the assessment of three different sized cases with realistic input factors affecting the net present value (NPV) model. We contribute to the ongoing discussion on the energy efficiency of DCs and provide a transparent assessment model for DC and district heating operators. We identified the positive NPV cases with high probability. The medium case has an NPV of 1.04 M€ (with uncertainty, the results range from −0.332 M€ to 2.57 M€). The large case has an NPV of 16.3 M€ (with uncertainty, the results range from 4.1 M€ to 30.2 M€). Both of these are clear-cut waste heat utilization investment proposals. The small case NPV is −48.5 k€ (with uncertainty, the results range from −264 k€ to 143 k€). The small case is sensitive to input factor values.

1. Introduction

The world requires energy and heat and is dependent on data centers (DCs). The majority of the global population lives in urban areas and is responsible for approximately 70% of the total primary energy usage. This share is expected to increase to 75% by 2030. In 2012, the heating and cooling of buildings consumed 50% of the total energy (European Commission, 2016). Nearly all this energy is from non-renewable sources (Zachary Woodruff, Brenner, Buccellato, & Go, 2014). The Paris (COP21) agreement is expected to increase the use of renewable energy sources and energy efficiency activities. In addition, the EU Energy Efficiency Directive aims to reduce energy consumption.

Global warming and the cost of energy have become a burden for e-businesses and created public interest towards DCs energy consumption. Currently, DCs consume about 1.1–1.5% of the world's total energy use (Ebrahimi, Jones, & Fleischer, 2014; Song, Zhang, & Eriksson, 2015). A 2017 study estimated the total amount of EU waste heat to be 3140 TW h (Stratego Project, 2016) (56 TW h is DC related (Ascierto, Lawrence, Donoghue, & Bizo, 2015)). Waste heat recovery reduces CO_2 emissions and other harmful gases (Ebrahimi, Jones, & Fleischer, 2015). However, supporting policies are needed to accelerate the waste heat utilization.

DCs are the main components of digitalization and cloud computing (Nada & Elgelany, 2014). The number of DCs has grown due to the increasing demand for data processing. Furthermore, the size of DCs has increased, and there is an ongoing trend in the consolidation of DCs into larger entities (Bardsiri & Hashemi, 2014; Song et al., 2015). The annual increase in DC energy consumption is estimated to reach 15–20% (Oró, Depoorter, Pflugradt, & Salom, 2015; Ebrahimi et al., 2014; Oró, Depoorter, Garcia, & Salom, 2015). This change in the DC industry favors the utilization of waste heat, as the heat sources are more significant and can offer a secured supply of heat. Climate change can also be considered a business opportunity for waste heat utilization equipment manufacturers (Gaudard, 2015).

More transparency and open communication to attain sustainable global business models and requirements are needed (Uddin, Alsaqour, Shah, & Saba, 2014). There are two strategies to improve DC sustainability: improving energy efficiency and increasing the use of renewable energy (N. Nada & Elgelany, 2014). Current energy efficiency activities in DCs include increasing power-feeding technology efficiency, aisle capping, reusing waste heat and fuel cell technology utilization (H. Endo et al., 2013).

Energy efficiency is not currently a dominant design criterion for DCs (Beloglazov & Buyya, 2010). Nevertheless, energy has become a

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critical factor in DC profitability and competitiveness (Afonso & Moreira, 2017; Zachary Woodruff et al., 2014). In addition, the increase in energy consumption will become a critical concern also to DC customers (S. A. Nada, Said, & Rady, 2016). Energy consumption in DCs is very high due to the increase in server density, 24/7/365 service hours (Afonso & Moreira, 2017; H. Endo et al., 2013; S. A. Nada et al., 2016), and because IT equipment manufacturers are integrating processors and computing power at an accelerated pace. It is estimated that server power consumption will double in the next three to four years following the current trend (Afonso & Moreira, 2017).

In urban areas, DCs profile as a waste heat source of reliable, low temperature, high capacity heat (Oró, Allepuz, Martorell, & Salom, 2018). Almost all of the information and communications technology (ICT) electricity consumption can be converted into heat (Ebrahimi et al., 2015; Zachary Woodruff et al., 2014). New DCs can be designed with an ability to capture waste heat and distribute it to nearby customers, such as homes, offices, swimming pools or greenhouses. A heat reuse solution allows DCs to sell the waste heat to a third party, such as a district heating (DH) operator. Solutions for waste heat utilization in DH have been studied for example in (Davies, Maidment, & Tozer, 2016; Wahlroos, Pärssinen, Rinne, Syri, & Manner, 2018; Wahlroos et al., 2018). The temperature of captured waste heat is limited by the electronics, which must remain below 85 °C most of the time. The quality and quantity of captured waste heat depend on the thermal management system being used. Captured heat from air-cooled servers is typically 35–40 °C, and thus it is sufficient for space heating as such. DH is more suitable for higher waste heat temperatures. Liquid cooling techniques provide waste heat temperatures of 50–60 °C.

DH is popular in the Nordic and Baltic countries, as well as in Russia and China, which have high heat demands and cold winters. In contrast to (Ebrahimi et al., 2014) where DC waste heat utilization in DH, in a retrofit case, was defined as a questionable solution, we argue, it is a very viable solution economically and ecologically. Utilizing DC waste heat in DH has been studied to have a positive impact on DH production in economic terms, as well as on the DC operator (Wahlroos et al., 2018). One of the most important benefits of a DH network is that it can adopt large amounts of heat, which make DC waste heat utilization possible for larger DCs. Two alternative business models have emerged: 1) DC operator invests and operates waste heat equipment, and 2) DH operator operates the equipment. The choice of a business model also affects the pricing of waste heat energy. In this study, we investigate the first alternative.

Little research has been published on the economic evaluation of waste heat utilization in the DC industry. It is unclear if DC waste heat recovery can be an economically solid investment and is it profitable to all DCs with varying size? This paper aims to provide an economic investment assessment of DC waste heat utilization using the net present value (NPV) model for three different sized DCs. The data in this model is based on empirical measurements of equivalent rack power consumption, investment prices of equipment and simulated heat market dynamics on a system level. The results together with the marginal-price demand side simulation, investment prices from already conducted projects and a transparent open source Monte Carlo simulation tool (GitHub, 2018) on input factor sensitivity are novel contributions to the researchers and industry stakeholders. In addition to the purely economic NPV analysis, we have calculated specific energy efficiency related metrics in our simulations. Calculated metrics are energy reuse effectiveness (ERE) and energy reuse factor (ERF), which are based on assumed PUE values for our case DCs.

The remainder of this paper is organized as follows. Section 2 describes the methods used in this study, Section 3 presents the results, and in Section 4 we discuss the results followed by the conclusions in Section 5.

2. Materials and methods

The capital expenditure (CAPEX) assessment decision criteria depend on the objective of the opportunity. Some CAPEX opportunities are accepted without quantitative criteria, such as investments in maintenance, pollution reduction, safety improvements, or complying with the legislation. Generally, CAPEX is subject to quantitative assessment, with the level of detail depending on the size and risk of the project and the managers' appetite for risk (Lane & Rosewall, 2015).

Financial analysis can be performed utilizing many models and tools. Researchers have categorized the investment assessment methods into five types; NPV methods, rate of return methods, ratio methods, payback methods, and accounting methods (Kumar, Sharma, & Tewari, 2015). The best practices for investment efficiency evaluation include net present value (NPV), internal rate of return (IRR), discounted payback period (PB) (Kvon, Khamidullin, Samysheva, Vaks, & Mararov, 2016; Lane & Rosewall, 2015), return on investment (ROI) (Afonso & Moreira, 2017; InvestingAnswers, 2018), total cost of ownership (TCO), and real option analysis (ROA) (Gaudard, 2015). In this study, we will use the NPV, IRR, discounted payback period and ROI. ROA is not considered, as it is not suitable for our purposes in the case of waste heat utilization.

Next, we will briefly go through the most common methods used for financial analysis of investments. In addition, we introduce the NPV model, related assumptions, a simulation of marginal cost based heat demand, and methods used for uncertainty analysis.

2.1. Financial investment analysis

Lucrative capital investments lead to the prosperity of an economy, providing solid reasoning to evaluate the NPV index (Kumar et al., 2015). NPV is the most frequently used method for assessing the economic effectiveness of an investment. It is especially suitable when making passive first-time investment decisions. NPV considers cash flows over an extended period of time (Adusumilli, Davis, & Fromme, 2016; Afonso & Moreira, 2017; Gaudard, 2015; Kumar et al., 2015; Matos, Bentes, Santos, Imteaz, & Pereira, 2015). NPV leads into better investment decisions because it recognizes a time value of money, depends solely on the forecasted cash flows, and all values can be added as they are present values (Brealey, Myers, Allen, & Mohanty, 2012). Decisions based on average cost can be 10% worse compared to NPV based decisions (Kumar et al., 2015). Finance theory endorses investment if NPV is positive with the chosen rate of return. Positive NPV can be reached when the present value of cash inflows exceeds cash outflows (Adusumilli et al., 2016; Brealey et al., 2012). The NPV model requires the following variables to be forecasted: 1) investments, 2) operating revenues, 3) operating costs, 4) economic life of the project, 5) inflation rate, and 6) interest rate (Afonso & Moreira, 2017; Brealey et al., 2012; Kumar et al., 2015). NPV is based on proven principles but contains many assumptions resulting in an inherent uncertainty. Actualized results may deviate from expected long-term values (Adusumilli et al., 2016).

To be able to compare an investment made to future cash flows, the present value (PV) of future cash flows is computed with a rate of return r (Afonso & Moreira, 2017; Henchoz, Weber, Maréchal, & Favrat, 2015). The r is dependent on the risk and the rate of return expected by investors from similar ventures (Kumar et al., 2015; Matos et al., 2015). In theory, r should be set with reference to a company's weighted average cost of capital (WACC). WACC takes into account the capital structure, debt, and equity of the company. In practice, r can be higher than WACC when there is a higher risk in the project compared to the company's operational risk level. There are as many r values as there are businesses and industries. In some related assessments $r = 5\%$

(Gaudard, 2015; Oró et al., 2018) was used, in the DH project $r = 6\%$ was used (Henchoz et al., 2015), and in the water management industry $r = 5\%$ (Adusumilli et al., 2016) was used. The Deloitte 2014 CFO survey found 90% of companies used an r value exceeding 10%, and half r exceeding 13%. A higher r can be used to compensate for uncertainty from the positivity bias in future cash flow estimations (Lane & Rosewall, 2015). NPV is a sum of these present value cash flows (Matos et al., 2015). Three general rules must be followed; 1) only cash flow is relevant, 2) cash flows need to be estimated on an incremental basis, 3) treatment of inflation needs to be consistent (Brealey et al., 2012).

Calculating NPV has four critical steps: 1) estimation of future operating free cash flows (OFCF), 2) estimation of a rate of return factor r, and discounting the future cash flows into the PV, 3) computing the NPV value, and 4) evaluating the results (Brealey et al., 2012). The NPV value is calculated from Eq. (1).

$$NPV = \sum_{i=0}^{n} \frac{OFCF_i}{(1+r)^i} \tag{1}$$

$i = 1. ..n\ years$

We also calculated the internal rate of return (IRR) (Brealey et al., 2012). It is used to estimate the profitability of investments. IRR is an r that makes NPV of an investment opportunity equal to zero (Afonso & Moreira, 2017; Matos et al., 2015). A project should be approved if the IRR of the project is higher than the selected rate of return factor (Lane & Rosewall, 2015). All investment opportunities with IRR below the risk-free rate are unprofitable under present market conditions (Gaudard, 2015). IRR value is calculated from Eq. (2). IRR is the r at which the PV of future cash flows equal the investment made (Afonso & Moreira, 2017).

$$NPV = \sum_{i=0}^{n} \frac{OFCF_i}{(1+r)^i} = 0 \tag{2}$$

$i = 1. ..n\ years$

$r = IRR$

To strengthen our analysis, we calculated the ROI percentages. ROI is an index representing the ratio between earnings and the amount invested (Afonso & Moreira, 2017). The higher the ROI%, the better the investment. Note that ROI does not take the time value of money into account as NPV does. Basic ROI% is calculated (InvestingAnswers, 2018) from Eq. (3):

$$ROI\ \% = \frac{Net\ Operating\ Profit\ After\ Taxes}{Investment} * 100 \tag{3}$$

Payback period is the inverse of ROI (Afonso & Moreira, 2017). It is time the project is expected to take to earn revenue equal to the capital cost within the discount period. It is calculated as the ratio between total CAPEX and the cash flow, taking into account the rate of return factor. The payback method does not take cash flows into account after the cutoff period (Matos et al., 2015). The payback period is often used together with the NPV analysis. A payback period of around three years is considered a reasonable level (Lane & Rosewall, 2015). The payback period is calculated with Eq. (4) (Matos et al., 2015):

$$PB = \frac{p + R_p}{R_p + R_{p-1}} \tag{4}$$

$p = time\ in\ years\ before\ the\ accumulated$

$discounted\ cash\ flow\ becomes\ positive$

$R_p = discounted\ cash\ flow\ accumulated\ in\ period\ p$

$R_{p-1} = discounted\ cash\ flow\ accumulated\ in\ period\ p+1$

The total cost of ownership (TCO) evaluates the economic impact of the use of the investment. It is used to assess the real total costs of building, owning and operating a facility. TCO is a sum of CAPEX, operating expenses (OPEX), replacement costs (REC) and residual value (RV). When REC and RV are equal to the assessment period, they can be discarded. We will not use TCO as a key performance indicator (KPI).

ROA allows longer-term considerations. It is useful in situations with high uncertainty and flexibility of possible outcomes. In ROA, a risk-neutral behavior is assumed. ROA provides a more optimistic outcome than NPV (Gaudard, 2015). We will not use ROA as a KPI.

2.2. NPV model for waste heat utilization investment

For NPV modeling, we made assumptions and simplifications: 1) a typical rate of return factor for a similar venture is 15% (Brealey et al., 2012), 2) a 10-year depreciation plan for the waste heat capturing and heat pump devices, 3) change in working capital is not relevant, 4) annual growth rate of power consumption decrease per rack is considered zero, 5) ramp-up time from initial capacity to full capacity is 24 months, 6) nominal cash flows are used for estimation, 7) tax rate is The Organisation for Economic Co-operation and Development (OECD) average 22.34% and tax-shield is not used, 8) the measured power consumption or 4.286 kW per rack is used for each case, 9) heat recovery rate is fixed at 97%, 10) employer costs, on top of monthly salary, are OECD average 14.4% (OECD publishing, 2017), 11) coefficient of performance of 3.75 is used for priming the heat, 12) the average salary annual base growth is 0,6% (Partington, 2017), 13) a maintenance specialist's monthly salary is 4000 €, and 14) a business manager's monthly salary is 6000 €.

In the following sections, we define the input factors and methods used in the NPV model. The construction phases of the NPV model are presented in Fig.1.

2.3. Phase 1: generic NPV model input factors

In the following sections, we provide reasoning for our NPV model generic input factors. These factors remain the same for all cases. The rate of return factor has been set to a level of 15%, which is a typical value for a project considered as an expansion of the existing business (Brealey et al., 2012). The investment into waste heat capturing equipment is made on December 31st, 2015, and the depreciation plan is set to 10 years. Due to the conservative nature of data centers on long-term investments, we have estimated depreciation plan of ten years for the investment based on an interview with a Finnish waste heat recovery system provider Calefa Oy (Porkka & Niiranen, 2018). The payback time is short in comparison to lifetime of the waste heat recovery equipment and infrastructure, which typically ranges around 15–20 years. Shorter payback time reduces the risks for the investment.

There are no products in stock and the payment period is the same

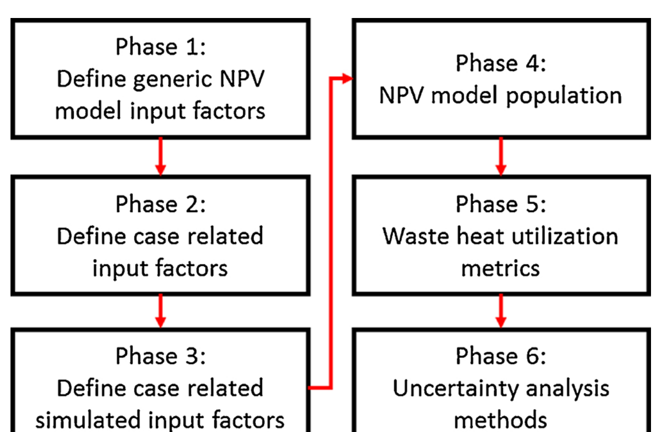

Fig. 1. NPV model phases.

as the invoicing period, resulting in a net effect of zero in working capital. The annual growth rate of power consumption per rack is considered zero in our NPV calculation, while the model allows yearly changes to the growth rate. The reasoning behind the zero growth is based on the simultaneous increase in the number of computations per kWh (Koomey, 2010) and the amount of data being processed (Mohanty & Routray, 2017). We assume a zero net effect. The flat rate is a source of uncertainty.

We use a ramp-up time of 2 years. The DC starts with initial setup, after which there is significant pressure to increase the capacity to its full potential, to make the DC business case positive. Running the facility under full capacity is an economic failure of the whole DC investment. We use nominal cash flows and do not consider the effect of inflation. Nominal cash flows are typically used for estimating the future cash flows. The tax rate of an average OECD corporation, 22.34%, is used (OECD, 2018). The tax-shield has not been taken into account to simplify the NPV model. All of the factors above have inherent uncertainty.

Several studies have investigated rack power consumption. In a 2014 study, per rack power consumption in a legacy DC was reported to be 7 kW, and in a modern DC 10–15 kW, and a rack full of blade servers 21 kW. In 2014, The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) estimated power consumption to be up to 60 kW per rack with an extreme density of IT-equipment, and 35 kW for a rack with an extreme density of computer servers (Ebrahimi et al., 2014). A 2015 study reported a traditional rack consumes 1–6 kW, and high-performance computing (HPC) racks of up to 30 kW of power (2015b, Oró, Depoorter, Garcia et al., 2015). A 2018 study reported power usage of 23.6 kW per rack (Oró et al., 2018). A 2016 study reported the power consumption of a typical low rack to be 3.5 kW (S. A. Nada et al., 2016). The high variance between the different power consumption per rack values can be the result of some studies using theoretical maximums rather than actual operative power consumption figures of racks in production.

When power densities of racks rise, cooling becomes a challenge. For a rack with low power density, the air flow rate is lower and cold air does not reach the servers in the upper cabinets of the rack, causing the temperature rise of these servers. At a high rack power density of 7 kW and above, the air flow rate is high. The high velocity of the air moves the air up with high momentum, and passes the servers of the lower cabinets, resulting in hot spots around these servers. In addition, high momentum air produces a cold air bypass between cold aisles to the hot aisle at the top of the rack (S. A. Nada et al., 2016), increasing the need for liquid cooling solutions with high power density racks (2015b, Oró, Depoorter, Garcia et al., 2015). We use the same measured power consumption per rack value in all cases. The measurement is taken from an actual service provider DC with multiple customers. The setup of the measured normative rack is presented in Fig. 2.

The rack contains two FX2 Dell blade chassis, four blade servers with two top-of-rack (TOR) switches each and nine Elastic Sky X (ESX) hosts. We measured the power consumption of the normative rack for one-week period. The power consumption daily average ranged from 4.217 to 4.355 kW. For the NPV model, we used the average power consumption of 4.286 kW. It is at the lower end of the range of the previously presented studies. Rack power consumption has a high impact on the NPV model, as cooling costs are not included in our economic assessment. Power consumption per rack is a source of uncertainty in our model.

For heat recovery rate, we use 97% as Lu et al. suggested (Lu, Lü, Remes, & Viljanen, 2011). The heat recovery rate contains uncertainty. We assume the annual base growth of salaries to be OECD eurozone 2017 forecasted average 0.6% (Partington, 2017) and naturally this is a source of uncertainty. To avoid linear growth of salaries and to simulate the real job market conditions, we added an independent and identically distributed (IID) random variable on top of the base value with the expected value of 1.6%. Based on an interview with Calefa Oy, a coefficient of performance (COP) value of 3.7 was utilized for priming the circa 35 °C waste heat to circa 80 °C (Porkka & Niiranen, 2018). This is a fair estimation, as the literature suggests COP values between 3.0–6.0 (Davies et al., 2016) depending on the temperature differences. However, it contains uncertainty. From the interview with the Calefa Oy, we identified the key roles required for the waste heat utilization operations phase. These roles include a maintenance specialist and a business manager. In a 2015 study, the average full-time job equivalent salary was 8719 €/month (Henchoz et al., 2015). We estimated the average monthly salary of a maintenance specialist to be 4000 € and 6000 € for a business manager. There are uncertainties also in the salaries. All case independent assumptions are presented in Table 1.

In the following subsection, we will first introduce the three cases and go through the assumptions we have made for each case. Secondly, we provide reasoning behind the key components of the NPV model: total revenue, cost of goods sold (COGS), other costs, and investments. Together these form the OFCFs, which are discounted to the PV. We will also present the sources of uncertainty in our model.

2.4. Phase 2: case related input factors

We have created three cases. The first case is a small DC with a maximum capacity of roughly 50 racks. This case represents a typical small-scale service provider DC or a local DC of a multinational company with a variety of digital services hosted and managed. The second case is a medium size DC with 500 racks. This case represents a typical

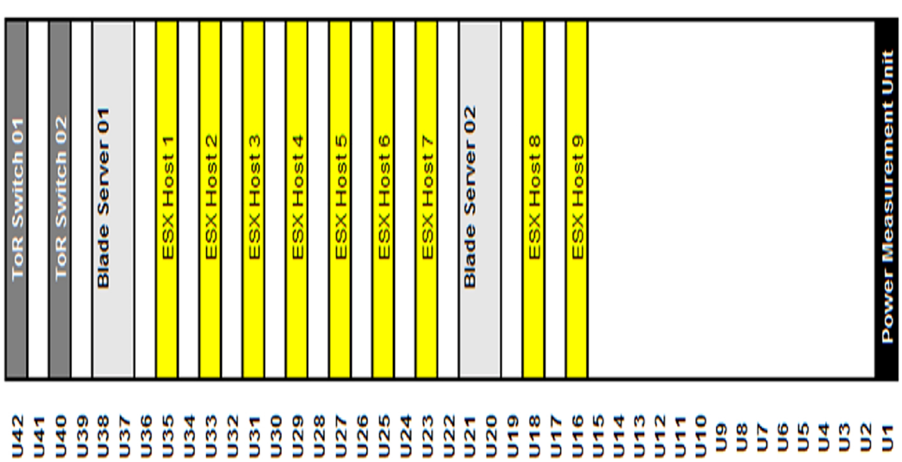

Fig. 2. Rack setup.

Table 1
Case independent assumptions.

General	Value	Reference
Rate of return	15.0%	(Brealey et al., 2012)
Depreciation plan (years)	10	(Porkka & Niiranen, 2018)
Power consumption per rack kWh increase/decrease	0%	Estimated
Tax rate	22.34%	(OECD, 2018)
Heat recovery rate	0.97	(Lu et al., 2011)
Salary employer costs factor	0.144	(OECD publishing, 2017)
Power consumption per rack kWh (measured)	4.286	Measured
The coefficient of performance (COP) for heat pump	3.75	(Porkka & Niiranen, 2018)
Salary annual base growth	0.6%	(Partington, 2017)
Maintenance specialist salary €/month	4000	(Porkka & Niiranen, 2018)
Business manager salary €/month	6000	(Porkka & Niiranen, 2018)

service provider DC, serving multiple customers with infrastructure as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS) services. The third case is a large DC with a maximum capacity of 5000 racks. This case represents a large service provider DC offering colocation, IaaS, PaaS, and SaaS fully managed services on an industrial scale for multiple customers and other service providers. We have assumed that all cases start with a greenfield DC with a space utilization rate of 20%, growing to the maximum capacity within 24 months linearly, with a fixed monthly growth rate of 7.25%. The growth rate and the initial utilization rate are sources of uncertainty.

The investment input in the NPV model should have realistic estimates of all the required equipment and include the latest cost of these components (Kumar et al., 2015). An investment into waste heat recapturing equipment includes the following components: 1) heat reuse equipment, 2) a connection to a DH operator, 3) setup project, 4) piping, and 5) heat pumps. In the small case, according to Calefa Oy, a small heat reuse device is sufficient. In a 2018 study (Oró et al., 2018), the cost of heat reuse equipment in a 118 kW DC was 55,000 €. It is lower than the investment price of a heat reuse solution (80,000 €) suggested by Calefa Oy (Porkka & Niiranen, 2018). The contents of these different setups are unclear, and therefore a comparison is not worthwhile. According to Calefa Oy, in larger cases, there is a marginal capacity increase between each 2 MW of rack power consumption (Porkka & Niiranen, 2018). After each 2 MW capacity increase in racks, a new block needs to be added. In the medium case, the 2 MW block is invested immediately. In the large case, the investment is divided into two years, aligned with the ramp up time.

The connection to a DH operator is a significant source of uncertainty. We assume a close connection between a DC and a DH operator. In demanding urban environments, setting up a connection can be hundreds of thousands of euros when streets need to be opened up. The project costs are estimations by Calefas reference projects. Projects depend on the DC and many other variables and are a source of uncertainty. The level of project uncertainty increases as the size of the DC increases. Waste heat reuse requires piping for the devices; we used prices for piping based on Calefa's references. The prices for heat pumps are estimated similarly to heat reuse devices; every 2 MW adds a new block. The small case can utilize smaller devices. The equipment prices contain uncertainty. According to Calefa Oy, retrofitting an old DC with waste heat capturing capability is typically a similar investment compared to a greenfield DC.

From the interviews with a waste heat capturing equipment manufacturer and distributor Calefa Oy, we estimated the required number of employees for steady state waste heat utilization operations phase. We claim that resourcing must be based on capacity to react to possible outages, so we added resources on top of the estimations by Calefa Oy.

Marketing is estimated to be a percentage of sales, and it is highest in the small case, as more marketing activities are needed to get contracts. In medium and large cases the amount of heat is higher and fewer large customers are needed. In addition, marketing activities are focused on the first two years, during which the contracts for waste heat utilization must be made. Marketing is a source of uncertainty.

In a 2015 study, the maintenance cost was considered to be 1–1.5% of the investment cost for the heat pumps, chillers, and boilers (Kumar et al., 2015). Maintenance cost is driven by labor, so it is expected to grow 1.2% annually (Henchoz et al., 2015; Kumar et al., 2015). Calefa Oy reported a maintenance cost of 200 €/month for the small case (3% of the investment including heat reuse equipment, piping, and a heat pump), 800 €/month for the medium case (1.38% of the investment), and 8000 €/month for the large case (1.40% of the investment) (Porkka & Niiranen, 2018). All figures are in the range of the aforementioned study results, thus contain uncertainty. Rent, computers, accounting services, and legal services are assumed as a fixed cost related to the size of the case. There is uncertainty in our estimations. Table 2 presents the cases and the key characteristics of each.

2.5. Phase 3: case related simulated input factors

DH pricing is one of the critical factors in the profitability of waste heat utilization. Due to the current DH system structure and pricing, it is typically not transparent how much DC operators pay for external heat (Wahlroos et al., 2018). In our simulations, we have decided to utilize a marginal-cost based, dynamic pricing method for waste heat.

Dynamic pricing is a novel approach for DH, which is currently not utilized in DH as it is. However, opening DH markets and introducing marginal cost based pricing has been foreseen as one of the most exciting development points in the near future. Dynamic pricing is commonly used for electricity trading, but dynamic pricing for DH has been suggested for example in (Difs & Trygg, 2009; Dominković, Wahlroos, Syri, & Pedersen, 2018; Mäkelä, 2014; Sun, Li, Wallin, & Zhang, 2016). Heat production units are dispatched according to the costs of production units. In dynamic hourly pricing, marginal prices reflect the marginal cost of the marginal unit in the system (Li & Hedman, 2015), i.e., the total hourly marginal cost is the marginal cost of the most expensive production technology. In dynamic pricing, every producer is paid according to the total hourly marginal cost. Typically, it is fossil-fuel based heat only boilers, which sets the hourly total marginal prices. With dynamic pricing, the price of heat would be higher when demand

Table 2
Case-specific assumptions.

Case	Small	Medium	Large
The initial number of racks	10	100	1000
Monthly growth rate	7.25%	7.25%	7.25%
Capital investment	115000	775,000	7370000
Depreciation/Amortization	11500	77500	737000
Maintenance specialist	0.2	0.5	1
Business manager	0.2	0.5	1
Marketing costs % of sales	5%	2%	0.5%
Maintenance service €/month	200	800	8000
Marginal rent, computers, accounting fees, legal fees per month	500	1500	15000

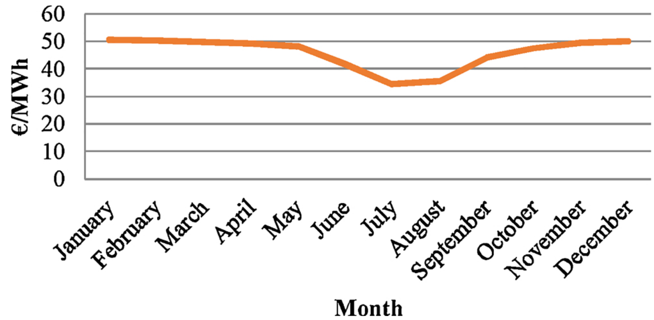

Fig. 3. Monthly marginal costs of DH production, which were utilized for waste heat pricing. Values have been simulated in the same method as in (Dominković et al., 2018). The x-axis denotes the months of one year. The y-axis denotes cost in €/MWh.

is higher, i.e., in the wintertime and lower in the summertime. As dynamic pricing depends on heat production technologies, the marginal prices would be different in separate DH networks.

We have used simulated hourly marginal costs in Espoo DH based on the modeling in (Dominković et al., 2018), which are further utilized in the NPV model. It was estimated that a DH operator would pay a DC operator according to marginal costs, minus a five €/MWh premium, which accounts for the network related costs of the DH network operator. Fig. 3 presents the monthly marginal costs used for waste heat pricing. Simulated hourly marginal prices vary between 14.7 and 57.8 €/MWh (see Appendix A Fig. A1 for hourly values).

Electricity price is one of the most significant factors in our NPV model. A 2015 study reported an average electricity price of 0.08 $/kWh (Ebrahimi et al., 2015), while a 2017 study used an average cost of electricity 0.11 €/kWh (Afonso & Moreira, 2017). A 2018 study conducted in Spain used an electricity price of 0.099 €/kWh. Similarly, the price for Switzerland was reported to be 0.15 €/ kWh in 2015, with an average rise of 1.2% in the price in 1980–2010. A global electricity price increase of 3% was estimated (Henchoz et al., 2015). The EU energy trends for 2030 report suggest a 5% yearly average increase in industrial electricity prices (Sevencan, Lindbergh, Lagergren, & Alvfors, 2016).

Electricity costs for priming the waste heat are calculated based on the estimates of monthly electricity prices by Statistics Finland (including energy fees, transmission fees, and taxes) (Statistics Finland, 2018). Larger customers typically have lower electricity prices. We have chosen different electricity prices based on the statistics for different sized data centers, based on their total consumption profile.

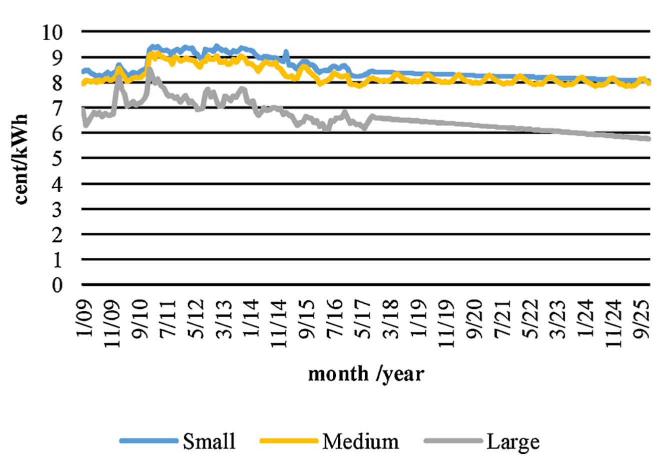

Fig. 4. Electricity price developments in different cases. The x-axis denotes month/year. The y-axis denotes the electricity price in cent/kWh. The prices include energy fees, transmission fees, and taxes (Statistics Finland, 2018).

Large electricity consumers typically secure their electricity by forwards or futures. Since futures may not be available upfront for ten years, we have extrapolated electricity prices for the simulated timeframe in the scenarios based on the development of the price of electricity between 2009 and 2017 in.(Statistics Finland, 2018). Fig. 4 presents the forecasted expected value development of electricity prices for the different cases. Electricity prices are expected to decrease rather than increase in our cases, and thus electricity prices contain uncertainty.

There is an issue regarding electricity costs for DCs in Finland which must be noted. Over 5 MW DCs have a lower tax level in Finland, i.e., 7.03 €/MWh compared to the regular 22.53 €/MWh electricity tax. However, data centers must own the heat pump to be entitled to the lower tax level.

The COP for heat pumps has been estimated to stay constant throughout the year. It has been estimated based on the assumption that waste heat would be supplied to DH at 80 °C. In reality, the COP value shifts during the year depending on DH supply and return temperatures. Also, waste heat could be supplied at a lower temperature during the summertime, which would increase the COP of the heat pump. However, we have estimated a constant supply temperature of 80 °C, which would be sufficient for approximately 80% of the hours or more in Finland.

2.6. Phase 4: NPV model population

2.6.1. Total revenue

In the case of waste heat utilization, the revenue originates from heat captured and sold to the buyer. The buyer could be a DH operator, a greenhouse, a spa or other user of waste heat. In our NPV model, we assume all waste heat is sold to a DH operator. Heat prices are simulated with Matlab. The total revenue is dependent on the number of racks, the power consumed per rack, the power consumed for priming, heat recovery rate and heat price. We calculated revenues on a monthly basis for each case separately using Eqs. 5–8, to take seasonal fluctuations of heat prices into account.

$$\text{Total energy consumed GWh/month} = \text{Number of racks} \times \text{Power consumed per rack kWh} \times (1 + \text{power consumption increase per rack}) \times 720\,\text{h} / 1000000 \quad (5)$$

$$\text{Total energy consumed for priming GWh/month} = \text{Total energy consumed GWh/month} \times \text{Heat recovery rate} / \text{COP} \quad (6)$$

$$\text{Heat captured} = \text{Total energy consumed GWh/month} \times \text{Total energy consumed for priming GWh/month} \times \text{Heat recovery rate} \quad (7)$$

$$\text{Total revenue} = \text{Heat captured} \times \text{Heat price} \quad (8)$$

The average price of heat for future years contains uncertainty. The total revenue for 2016 is presented in Appendix B, Table B1. The values for 2017–2025 were calculated in the same manner.

2.6.2. Cost of goods sold

The COGS should only include direct costs related to the generation of the revenue (Kumar et al., 2015). There are several indirect and direct costs related to any business opportunity. Therefore we want to isolate the COGS related only to the waste heat business directly. COGS include employees directly working with waste heat capturing business processes, electricity costs incurred by improving the temperature from 35 °C to 80 °C, and the price of electricity. We calculated monthly COGS for each case separately. The Eqs. (9–12) were used to calculate the total COGS per month.

$$\text{Cost of Maintenance employees} = \text{Number of maintenance specialists} \times \text{Maintenance specialists salary} \times \text{Salary employer cost factor} \times \text{Annual growth of salary} / 12 \quad (9)$$

Cost of Business employees = Number of business managers * Business managers salary × Salary employer cost factor × Annual growth of salary / 12 (10)

Total cost of priming = Total energy consumed for priming GWh/month (5) × Electricity price €/GWh/month (11)

Total COGS = Cost of Maintenance employees + Cost of Business employees + Total cost of priming (12)

The electricity used for priming is taken from a technical specification, thus introducing uncertainty. The electricity price projection for future years contains uncertainty. The total COGS for 2016 is presented in Appendix B, Table B2. The values for 2017–2025 were calculated in the same manner.

2.6.3. Other costs

In addition to the direct costs, we have to include relevant allocated costs to create a realistic NPV model and cash flow projections. Other costs include marketing costs, maintenance fees from equipment manufacturers, rent, computers, and accounting and legal fees. Maintenance fees are gathered from the actual maintenance service conducted by Calefa Oy. Marketing is assumed relative to revenue. The rest is assumed to be fixed marginal monthly recurring costs. The *Total other costs* have been calculated using Eqs. (13,14). The *Total other costs* for 2016 is presented in Appendix B, Table B3. Values for 2017–2025 were calculated in the same way.

Marketing costs = Total revenue * Marketing costs % of sales (13)

Total other costs = Marketing costs + Maintenance service fee + Marginal rent, computers, accounting fees, legal fees per month (14)

2.6.4. Investment

The total investment is a sum of all costs incurred. We assume all costs are activated to a balance sheet. With the small and medium cases, all investments were made in 2015. With the large case, in 2015, the connection to a DH operator, piping, project costs and one-third of the heat reuse and heat pump investments actualized. The other two-thirds actualized between 2016 and 2017. Table 3 presents the investments required for each case.

2.7. Phase 5: waste heat utilization metrics

Objective, standardized monitoring and measurement of energy efficiency are needed (Jeong & Kim, 2014; Lajevardi, Haapala, & Junker, 2014). There are weak signals from DC operators using the energy reuse efficiency (ERE) and energy reuse factor (ERF) to indicate how much waste heat is utilized outside of the DC facility. Energy efficiency and energy consumption metrics are essential. Unfortunately, there is a new DC phenomenon called the metrics sprawl. Power consumption, overall availability, and energy efficiency have become the targets of this sprawl (2015b, Oró, Depoorter, Garcia et al., 2015). Transparency in metric results is essential for large-scale adaptation of waste heat utilization.

The Green Grid and the International Organization for Standardization (ISO) have proposed the ERF. The ERF is defined as the outside reuse of DC waste heat. ERF is calculated as the ratio of energy reused divided by the sum of all energy consumed in a DC. The total DC energy consumed includes power delivery, UPS systems, switchgear, PDUs, generators, cooling systems, lighting and other supporting systems. Transfer losses are not included. The DC industry and standardization use ERF to quantify the external waste heat usage of DCs. ERF values higher than 45% are found in a few studies conducted (Henchoz et al., 2015). ERF is calculated with the Eqs. (15,16):

$$PUE = \frac{E_{DC}}{E_{IT}} \tag{15}$$

$$ERF = \frac{E_{Reused}}{E_{DC}} = \frac{E_{Reused}}{E_{IT} * PUE} \tag{16}$$

ERE has been introduced to measure waste heat capturing strategies (Uddin et al., 2014). ERE is a modification of a widespread PUE metric (Patterson, Tschudi, VanGeet, & Azevedo, 2011). ERE is calculated with the following Eq. (17):

$$ERE = \frac{E_{Cooling} + E_{Power} + E_{Lighting} + E_{IT} - E_{Reused}}{E_{IT}} = (1 - ERF) \times PUE \tag{17}$$

Power consumption distribution of a 200 kW DC was; IT 58.3%, cooling 37.1%, and lighting and others 4.6% (Afonso & Moreira, 2017; Ebrahimi et al., 2015). In 10 random DCs, the range of power consumption was: IT 45%, cooling from 30% to 55%, power distribution 13% and lighting 3% (Song et al., 2015). Several recent studies suggest that on average 40% of the power is consumed by cooling (S. A. Nada et al., 2016; Oró, Depoorter, Garcia et al., 2015, 2015b; Zachary Woodruff et al., 2014). Based on these results, the power usage effectiveness value (PUE) is within the range from 1.72 to 2.22. We calculated ERF and ERE for each case with the assumed PUE.

2.8. Phase 6: uncertainty analysis methods

We present a comprehensive sensitivity analysis to meet the validity objective of the results. The aim is to identify the critical parameters influencing the decision-making process and to quantify the degree of influence (S. F. Santos et al., 2017). As a definition, uncertainty in information means incomplete or inaccurate information. Similarly, for an investment or a project, risk means the actualization of conditions resulting in unwanted consequences (Kvon et al., 2016). Sensitivity analysis is the method to increase the reliability of the NPV model results. In a sensitivity analysis, the impact of a factor change to the outcome of the model is investigated (Kvon et al., 2016). As a rule of thumb, The United Nations Industrial Development Organization (UNIDO) methods suggest changing critical parameters within the range from -20% to +20% (Kvon et al., 2016). We have used this method whenever no better information was available on the uncertainty.

Sensitivity analysis includes the following steps: 1) definition of the most probable and influential input factors, 2) NPV is calculated with the Expected scenario input parameters, 3) NPV is calculated in a sequence when the primary input factors change, and 4) the results are summarized into a table and sensitivity is evaluated per each factor (Kvon et al., 2016). Drawbacks of sensitivity analysis include: 1) it does not include all circumstances influencing investment decision, and 2) factors may not be discrete but instead have a correlation dependence on each other (Kvon et al., 2016). Alternative methods include the elasticity coefficient measurement. The elasticity coefficient measures a change of one unit in the input factor and the corresponding impact on the output value of the model. If the change in the output is more than the change in the input factor, it is considered elastic. If less, it is inelastic (Kvon et al., 2016).

Another alternative to sensitivity analysis is the scenario analysis method. In the scenario analysis method, alternative options with an

Table 3
Total investments for each case.

Case	Small	Medium	Large
Heat reuse	10000	90000	990000
Connection to DH	20000	50000	400000
Project	15000	30000	150000
Piping	10000	30000	330000
Heat pump	60000	575000	5500000
Total investment	115000	775,000	7370000

actualization probability of each option are investigated. Commonly three different scenarios occur; optimistic, expected, and pessimistic (Kvon et al., 2016). The scenario analysis method includes the following steps: 1) develop possible scenarios for the investment, 2) define the NPV in each scenario, 3) define the probability of implementing the scenario, and 4) calculate the expected NPV by taking probabilities into account (Kvon et al., 2016).

We present all factors with estimated uncertainty levels influencing the NPV model output in Appendix C, Table C1. All factors are assumed to be discrete and do not have any correlation between the two factors. Meaning that even though all factors are subject to uncertainty and variability, the variation or uncertainty of one factor is entirely different from that of another factor (S. F. Santos et al., 2017). The uncertainty of three factors increases as time advances. We identified the following factors with increasing uncertainty: power consumption per rack growth, heat price and electricity price. For these factors, we added an annual growth to uncertainty. It is far more uncertain to predict heat and electricity prices for 2025, compared to 2019 for example.

We investigated the simultaneous effect of variability of the most significant factors with a Monte Carlo simulation on the five most significant factors affecting the NPV model outcome. The Monte Carlo simulation generates multiple scenarios for representing possible realizations of uncertainties (Wu, Shahidehpour, Alabdulwahab, & Abusorrah, 2015). The simulation was coded with Python. We modeled a simplified NPV model for the simulation. The factors included in the simulation were heat price, electricity price, COP, the rate of return and total investment. We used the Expected scenario values as input for the simulation. We made the following simplifications to the NPV model: 1) tax shield is not used, 2) all values are averaged and aggregated to year level, 3) the four separate parts of the investment project are aggregated to one total investment, 4) ramp-up time is taken into account as an average number of racks during a 10 year period, and 5) the medium case was used to populate other case-specific factors with multipliers to two remaining cases. The fixed input variables, case-specific variables, simulated variables with ranges, and the total number of possible combinations of factor values, are presented in Appendix C, Table C2.

We have run the simulation 3 million times. Utilizing averages across the time frame benefits the revenue during ramp-up time, thus gives a penalty for costs. The rate of return has a more significant effect as time advances, thus creating small uncertainty to the distribution. The distribution of each case is within the Min and Max of the range for the scenario.

3. Results

The results of our NPV model Expected scenario are presented in Appendix D, Table D1. Section 2 defines the NPV input variables that form the Expected scenario results. Based on these results, the small case appears to create a negative NPV, indicating an unprofitable investment with the assumptions and inputs given to the model. Both medium and large cases give a positive NPV. Nevertheless, the small case has a positive ROI, indicating the case being sensitive to changes in input variables, such as the rate of return factor. The IRR of the small case is 7.05%, which is below the expected rate of return. It should be noted that IRR must be above the company WACC, preferably above the rate of return.

The discounted payback period in the small case is over than ten years, which was set as the scope of our assessment. We set all factors to minimum and maximum to investigate the investment KPI range. The total uncertainty in the small case [Min, Max] was [322%, -458%]. The negative NPV in the Expected scenario provides non-intuitive results (i.e., negative values for Max scenario). The uncertainty is considerable, and the small case is sensitive to input factor variation. Similarly, both the medium [-148%, 130%] and large [-87%, 75%] cases imply improved sensitivity against uncertainties when the case size increases. The medium case has a positive NPV in the Expected and Max scenarios. The large case is positive even in the Min scenario. The discounted payback period for medium and large cases varies from 1.82 to 5.14 years depending on the scenario and case. The ranges of investment assessment KPIs are presented in Table 4.

We analyzed discounted cash flows (DCFs) and earnings before interests and taxes (EBIT) for each case with Expected, Min and Max scenarios to visualize the effect of uncertainty in results as a function of time. Fig. 5 shows the increasing uncertainty as a function of time.

Variation between Min, Expected and Max scenarios are large. In the large case, all KPIs are positive in all scenarios; it is not sensible to input factor variation from the investment decision-making perspective. Fig. 6 summarizes different KPIs between scenarios and cases.

Table 5 presents energy efficiency metrics in different cases. We estimated initial PUE values for the DCs without waste heat utilization based on the literature review. Small, medium and large cases were considered to have initial PUE values of 2.2, 1.97, and 1.72, respectively. Electricity consumed by a heat pump increases the total power consumption of a DC. ERF values for DCs vary between 0.5–0.62, which indicates that over 50% of the total energy consumption can be recovered via waste heat recovery from processing load.

3.1. Uncertainty analysis results

We investigated the combined impact of the most significant factors in our NPV model. The investigation was carried out by programming a simplified Monte Carlo simulation and randomizing the five factors under investigation. The five identified factors with ranges [minimum, maximum, step] were: heat price €/MWh [36.7, 55.1, 10], electricity price €/MWh [64.5, 96.8, 10], rate of return [0.18, 0.12, 0.001], total investment factor [0.8, 1.2, 0.01] and COP [2.813, 4.687, 0.1]. The total number of possible permutations is approximately 255 billion. We simulated 3 million rounds, approximately 1 million rounds for each case. The Monte Carlo simulation NPV distributions for all cases have been presented in Fig. 7.

The small case NPV output is negative with significant probability. All distributions follow the normal distribution to a large extent. The expected value of normally distributed results is the mean of the results as n approaches infinity. The expected value of distribution in the small case is -40.04 k€ with the standard deviation of 50.79 k€. These results are aligned with the Min and Max scenarios for the small case. The expected value of the simulated small case is 8445 € higher than in the Expected scenario, which is understandable as only the five most significant factors were simulated. In addition, the range of simulated results is within the Min and Max scenarios. Similar results apply to all cases. Table 6 presents the key characteristics of simulations for all distributions.

3.2. Validity of results

The NPV model inherits uncertainty. We have defined uncertainty levels to all factors, out of which three factors have increased uncertainty as a function of time. The total uncertainty level is high. Nevertheless, the high probability NPV positive cases can be identified. The small case is NPV negative with Min and Expected scenario factor values and positive with Max scenario factor values. Therefore, it is sensitive to input factor values. This sensitivity is a challenge from a decision-making perspective. The medium and large cases are clear-cut investment proposals. The Expected scenario values from each case can be considered valid.

4. Discussion

Investment-decisions depend on the risk of the project and estimated future cash flows. We created an NPV model to provide transparency into the economic aspects of waste heat utilization. The

Table 4
KPIs for each scenario.

	Scenario Min			Scenario Expected			Scenario Max		
KPI	S	M	L	S	M	L	S	M	L
NPV (thousand euros)	−264.1	−332.0	4120.0	−48.5	1041.4	16329.2	143.8	2569.0	30152.6
ROI	−309%	51%	419%	56%	412%	1046%	408%	885%	1892%
IRR	NA	8.01%	30.29%	7.05%	38.57	58.54%	34.71%	67.12%	92.89
Payback period (years)	> 10 years	> 10 years	5.14	> 10 years	3.72	2.75	4.11	2.14	1.82

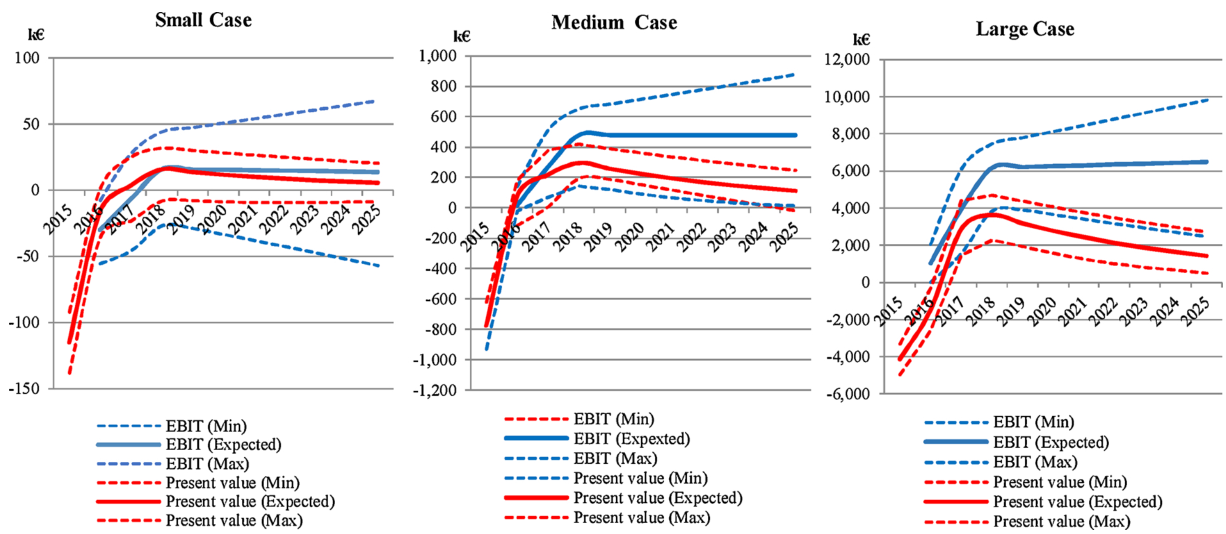

Fig. 5. Min, Max and Expected scenario EBIT and PV with uncertainties in different cases.

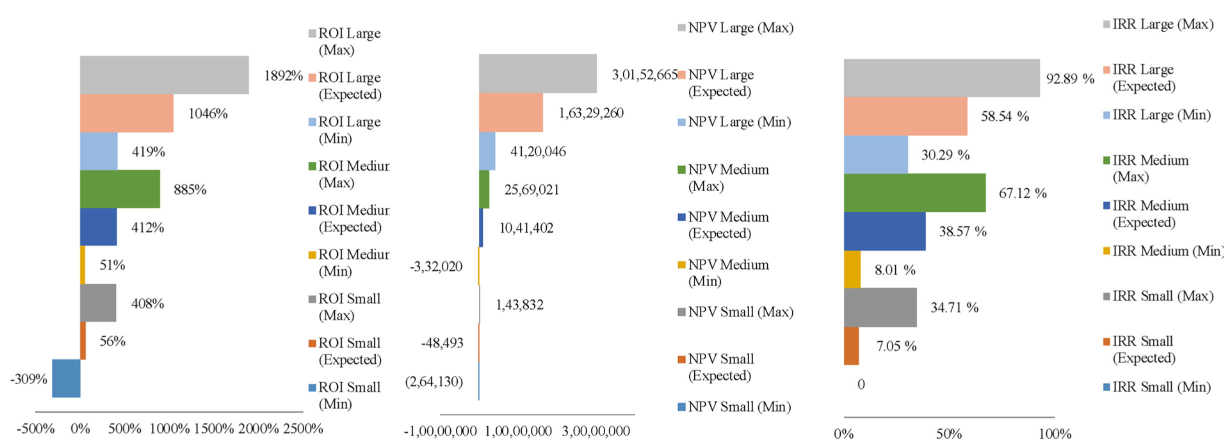

Fig. 6. Min, Max and Expected scenario ROI (left), NPV (middle) and IRR (right) with uncertainties.

Table 5
Energy efficiency metrics in the case of waste heat utilization.

	Small case PUE 2.2	Medium case PUE 1.97	Large case PUE 1.72
PUE with waste heat utilization	2.48	2.23	1.98
ERF	0.5	0.55	0.62
ERE	1.25	1	0.75

profitability of the waste heat recovery investment is positive inside the full range of uncertainty in the large case. In the medium case, the extremely pessimistic factor values result in a negative NPV. Nevertheless, even in the pessimistic scenario, the IRR is 8.02%, which is higher than the WACC in many companies. Therefore, the investment can still be worthwhile from ecological sense.

The small case seems problematic. The Expected scenario NPV value is negative; the Min scenario is hugely negative, only the extreme Max scenario factor values result in a positive NPV. In addition, the distribution of the NPV values when changing the most significant factors randomly within the range of uncertainty results in a negative NPV value with high probability. The small case is susceptible to factor variations. Therefore, it is challenging to make an investment assessment on the small case. It contains risk. In our model, we assume that all waste heat is sold to a DH operator. In the small case, alternative customers for waste heat could be considered. Customers, which could utilize low quality heat without priming for example. These alternative waste heat customers could include internal office space heating, greenhouses, spas, or industrial processes requiring only low-quality heat. Another possibility could be clustering many small size DCs to provide jointly more heat to DH. Whether this shows to be a technically

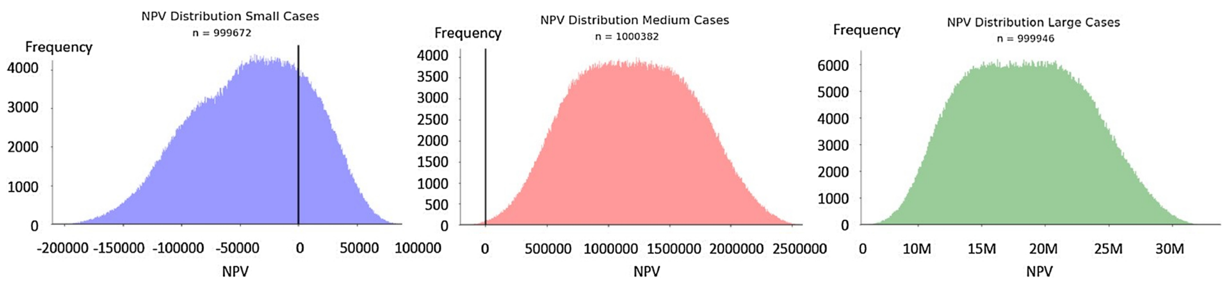

Fig. 7. Monte Carlo NPV distributions for cases.

Table 6
Distribution characteristics.

Distribution	n	Min	Max	Mean	Standard deviation
Small case	999672	−210649	91747	−40048	50785
Medium Case	1000382	−204031	2620834	1203092	487299
Large case	999946	5523535	32483519	18462779	4868941

and economically feasible option, from the perspective of connecting to a DH operator, should be investigated.

The relative effect of uncertainty on decision-making decreases when the size of the case increases. Whenever a more specific estimation of uncertainty was not available, we utilized the UNIDO method [-20%, 20%] for each input factor in our NPV model. There was uncertainty in our uncertainty estimation. To overcome infinite regression, we used annually increasing uncertainty for three factors. It should be noted; for the sake of simplicity, we do not assume a decrease in the number of racks during the observed period. Naturally, this is possible in reality. Overall, although the NPV model contains uncertainties, it seems credible to assess the small case as unprofitable and the medium and large cases profitable with high probability.

Uncertainty for depreciation plan was not considered in our simulations, but the NPV model enables extending the time frame. Due to the fact that NPV emphasizes years closer to the investment, prolonging payback period of the investment affects results slightly. In truth, data centers should consider longer depreciation plans to match the lifetime of equipment.

One important aspect is the availability of data. In our study, we have gathered data from literature and from waste heat service provider, but actual figures are not widely available in public for every parameter, and thus uncertainty ranges may have been overestimated. Additional data would improve the accuracy of the model, and with better accuracy, the profitability of investment could be analyzed more clearly. Therefore, service providers and district heating companies should be encouraged to publish more data openly. We have published our simulation code to GitHub (GitHub, 2018) for further use with more detailed and case specific data.

4.1. Heat price

As the results of the NPV model suggest, the heat price is one of the most critical factors in the simulations. As it was estimated that heat would be priced with marginal-cost based pricing, the results may differ from the actual heat prices offered by the energy companies. In fact, the actual heat prices might be far lower if the energy companies try to take advantage of the waste heat provider. For example, a DH company in Finland has offered heat prices of 15–28 €/kWh a few years back. However, the heat was required to be at least 66 °C, which is not enough for the supply-side of the DH network throughout the winter. Therefore, higher prices can be assumed if heat is continuously at 80 °C or more.

In June 2018, a large-scale energy utility Fortum started to publish their waste heat purchase prices as a forerunner in Finland (Fortum Ltd., 2018). They publish the prices for three different Finnish DH networks, one of which is the Espoo DH network. In Espoo, the prices are available for heat suppliers with a load below five MW. Heat prices vary based on weather and outdoor temperature, and whether the heat is sold to the supply or the return side of a DH network. For the supply side, prices range from 50 €/MWh at outdoor temperatures below −8 °C to 15 €/MWH at temperatures above 20 °C. To analyze the profitability of public prices in Espoo, we ran a Monte Carlo simulation for the medium case using the purchase prices offered for the Espoo network. The mean NPV in the medium case was -167609 € with the results ranging from -1299103 € to 648,820 €. The standard deviation was 283,710 €. The results show that the medium case is likely unprofitable with public prices. However, few issues require additional consideration. Firstly, Fortum has not provided an actual temperature requirement for the supply side, and thus it is likely that primed waste heat temperature to 80 °C is higher than Fortum's standards, and thus the temperature of the heat could be lower meaning the heat pump COP could increase. Secondly, in this simulation, we assumed all heat is primed with a heat pump and sold to the network. However, with Fortum's prices, it would not be beneficial to sell heat when the outside temperature is high since it is more expensive to increase the temperature compared to the purchase price. Therefore, the timing of selling heat should be analyzed more accurately, and it should be considered whether waste heat can be sold to the return side without priming.

It must be noted, that DH is not the only option for waste heat utilization, especially in Central Europe, where DH networks do not exist in such a large extent. DC waste heat could replace DH consumption or own heat production, e.g., in a housing block. Waste heat can be more profitable compared to DH when the waste heat replaces individual natural gas boilers in homes. In Finland, a weighted-average consumer price of DH in 2016 was 74.8 €/MWh (Finnish Energy, 2017). Considering the small case, a DC could replace its own facility DH consumption. Using the 74.8 €/MWh price, we ran the same Monte Carlo simulation. The uncertainty in the consumer DH price was considered 10%, as it is less volatile compared to selling waste heat to DH. The mean NPV in the small case increased to 189,000 € with results ranging between 61,700 € and 329,300 €. The standard deviation was 43,000 €. It must be noted, that in reality waste heat would not be primed to 80 °C for self-consumption, and thus heat pumps would have better COP values, which would enhance the profitability of self-consumption. Annual heating energy demand for a commercial building in Finland is approximately 182 kW h/m^2 (Statistics Finland, 2018), and thus the small case could supply heating for a 12,500 m^2 of commercial buildings. In most cases, the small case DC cannot utilize all excess heat. Therefore, the DC should be connected to an office building to replace individual heat production, for example. Another challenge is that with self-consumption seasonal changes have more effect compared to the aggregated heating demand in DH.

4.2. Electricity price

The electricity price is another critical factor based on the uncertainty analysis. We have estimated decreasing electricity prices based on the current trend, although some studies have suggested growing electricity prices, at least on the small consumer side. Especially, electricity transmission prices are likely to increase in the future due to legal obligations for transmission system operators to invest in the security of electricity transmission according to the Electricity Market Act, which was implemented in 2013 (Ecolex, 2018; Energy Authority, 2017). Industrial consumers compete on electricity prices in different countries; thus, the governments may want to provide lower taxation to industrial consumers to maintain competitiveness. It is hard to estimate how electricity prices develop for the largest consumers. For example, Sweden has lowered electricity taxes for data centers to a lower level than Finland (Pöyry, 2018). Nonetheless, Nordic countries currently have lower electricity prices than most Central European countries, and therefore, the profitability of waste heat utilization in other countries tends to be less.

4.3. Case Germany

To analyze the effects of heat and electricity prices, we considered the effects of different heat and electricity prices for a small case DC in Germany. Germany occupies many DCs and Frankfurt is the second largest DC market in Europe, where the estimated total energy consumption was up to 12 TW h in 2015 (Bertoldi, Avgerinou, & Castellazzi, 2017). The electricity price for a DC consuming annually 8.5 GW h of electricity was estimated to be 142.4 €/MWh (Pöyry, 2018), while the DH price for the large customer was 66.38 €/MWh (Statista, 2018). Large-scale electricity consumers may save up to 90% of their transmission costs in Germany, if they consume over 10 GW h and run over 8000 h annually (Pöyry, 2018). Using the 66.38 €/MWh heat price and 142.4 €/MWh electricity price, we ran the same Monte Carlo simulation. The uncertainty in the heat price was considered 10%. The mean NPV in the small case was 12,100 € with results ranging from -182000 € to 161,000 €. The standard deviation was 49,800 €. If a small case DC in Germany could consume or sell waste heat for the consumer price of DH, waste heat could be marginally profitable, although electricity prices are far higher for small-scale DCs. However, heat demand for facilities consumption is far lower in Germany, and during summertime heat could not be efficiently utilized even at the amount of waste heat produced in the small case.

4.4. Metrics

Results showed that PUE is not a sufficient metric for data centers reusing waste heat. PUE values increase due to the increased electricity consumption of the heat pump and therefore a DC with waste heat utilization should not use PUE. However, if ERE was used as a standard method, the cases could be considered more efficient than data centers which do not reuse heat. We did not take into account that heat could be recovered from other sources than the electricity consumption of processors. In reality, waste heat could be captured from the cooling system, and a heat pump could be used to produce cooling energy for the data center. This could change the efficiency metrics radically since up to 90% of the total energy demand could be recovered. Finally, it should be calculated what type of heat production waste heat replaces in a district heating system, as well as the emission factor of additional electricity consumption, to assess the total environmental effect of waste heat utilization.

4.5. Role of employees

The small case is sensitive to input factor values. We simulated with employees set to zero. The small case resulted in a mean NPV of 79,500 € with results ranging from -60000 € to 222,000 €. From these results, we conclude the small case is more dependent on fixed costs compared to the two other cases. The number of employees needs to be evaluated with consideration, as the impact on the distribution results is high.

4.6. The impact of cloud strategy

Any kind of contractual commitments to sell and deliver waste heat could potentially limit strategic options for a DC operator. These commitments could impact the DC operator's public cloud strategy. The decision to move workloads to public cloud reduces the need for local computing, thus reduces the amount of produced heat and revenue generated by selling this excess waste heat. When marginal are low, this extra revenue could make a difference in the decision-making process. Commitments can also be seen as a lock-in into a particular type of business model.

In future studies, researchers could investigate how the following aspects change the NPV model output: 1) the use of on-site renewable energy sources for priming, 2) the effect of using uninterruptible power supply (UPS) as a source of electricity, 3) the effect of waste heat reuse on the cash flow of a DC operator in the business case of transforming workloads into public cloud, and 4) the content of the bilateral commercial agreements between DC and DH operators.

5. Conclusions

The IT industry consumes vast amounts of energy. One possible strategy to promote energy efficiency involves reusing waste heat generated by the racks full of servers and other telecommunications equipment. We conducted an investment assessment for waste heat utilization in three different size cases, namely small, medium and large.

The small case NPV was -48500 € (with uncertainty, the results range from -264000 € to 143000 €). The Monte Carlo simulations on the most significant factors reveal the small case results in a negative NPV with high probability. Therefore, investing in waste heat utilization equipment has no rational economic grounds. The amount of heat captured and sold to DH operators will not cover the costs of the waste heat utilization equipment. To make the small case profitable, alternative uses for waste heat must be sought or otherwise discard the investment. Naturally, there are also other investment decision criteria than economics. Companies can make investments even if the case is not profitable for the company. Investments could be made for image or ideological reasons. Nevertheless, these are not within the scope of this paper.

The medium case has an NPV of 1.04 M€ (with uncertainty, the results range from -0.332 M€ to 2.57 M€). The large case has an NPV of 16.33 M€ (with uncertainty, the results range from 4.12 M€ to 30.15 M €). The medium and large cases can be considered profitable business opportunities and should result in a decision to invest in a waste heat reuse solution.

The NPV model contains uncertainties, and the results must be viewed with a range of results, rather than a single result. We described the NPV model population in detail, giving the DC or DH operator an opportunity to change the input parameters, uncertainties, and assumption to match their business case. Regarding the active discussion on the economic viability of DC waste heat utilization, we contribute a transparent investment assessment model for both DC and DH operators.

Declarations of interest

None.

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Appendix A

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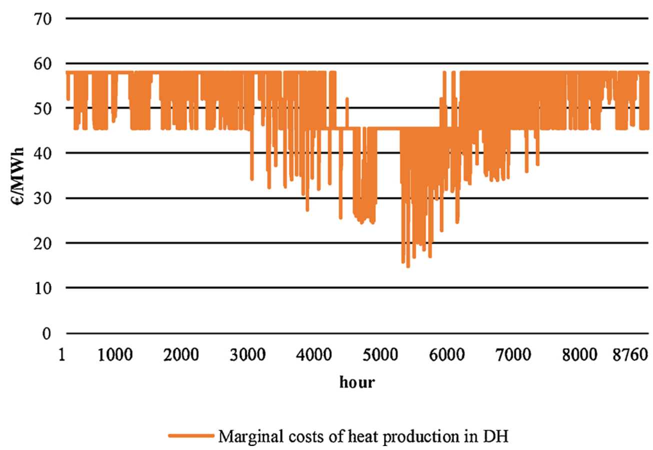

Fig. A1. Annual hourly marginal costs of DH production, which were utilized for waste heat pricing. The x-axis denotes the hours of one year. The y-axis denotes cost in €/MWh.

Appendix B

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Table B1
Total monthly revenue for each case in 2016.

CASE SMALL												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Number of racks	10	11	12	12	13	14	15	16	18	19	20	22
Total power consumed (kW)	42.9	46.0	49.3	52.9	56.7	60.8	65.2	70.0	75.0	80.5	86.3	92.6
Total power consumed (GWh/month)	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.06	0.07
Total power consumed for priming (GWh/month)	0.0080	0.0086	0.0092	0.0098	0.0106	0.0113	0.0121	0.0130	0.0140	0.0150	0.0161	0.0172
Heat captured (GWh)	0.0379	0.041	0.044	0.047	0.050	0.054	0.058	0.062	0.066	0.071	0.076	0.082
Heat price €/GWh/month	50700	50200	49,800	49300	48300	41600	34500	35400	44000	47400	49600	50000
Total revenue	1922	2041	2172	2306	2423	2238	1991	2191	2920	3374	3787	4094
	50700	50200	49,800	49300	48300	41600	34500	35400	44000	47400	49600	50000
CASE MEDIUM												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Number of racks	100	107	115	123	132	142	152	163	175	188	201	216
Total power consumed (kW)	429	460	493	529	567	608	652	700	750	805	863	926
Total power consumed (GWh/month)	0.31	0.33	0.35	0.38	0.41	0.44	0.47	0.50	0.54	0.58	0.62	0.67
Total power consumed for priming (GWh/month)	0.08	0.09	0.09	0.10	0.11	0.11	0.12	0.13	0.14	0.15	0.16	0.17
Heat captured (GWh)	0.38	0.41	0.44	0.47	0.50	0.54	0.58	0.62	0.66	0.71	0.76	0.82
Heat price €/GWh/month	50700	50200	49,800	49300	48300	41600	34500	35400	44000	47400	49600	50000
Total revenue	19223	20414	21719	23060	24230	22382	19908	21908	29205	33742	37868	40941
CASE LARGE												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Number of racks	1000	1073	1150	1234	1323	1419	1522	1632	1751	1877	2014	2160
Total power consumed (kW)	4286	4597	4930	5287	5671	6082	6523	6996	7503	8047	8630	9256
Total power consumed (GWh/month)	3.09	3.31	3.55	3.81	4.08	4.38	4.70	5.04	5.40	5.79	6.21	6.66
Total power consumed for priming (GWh/month)	0.80	0.86	0.92	0.98	1.06	1.13	1.21	1.30	1.40	1.50	1.61	1.72
Heat captured (GWh)	3.79	4.07	4.36	4.68	5.02	5.38	5.77	6.19	6.64	7.12	7.63	8.19
Heat price €/GWh/month	50700	50200	49,800	49300	48300	41600	34500	35400	44000	47400	49600	50000
Total revenue	192232	204136	217191	230599	242301	223820	199077	219080	292045	337422	378681	409411

Table B2
The total cost of goods sold for each case in 2016.

CASE SMALL												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Maintenance people	915	917	919	919	921	923	925	926	927	927	929	930
Business Manager	1373	1375	1378	1380	1381	1382	1383	1385	1386	1388	1390	1392
Electricity for priming GWh/month	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Electricity price €/GWh/month	84900	83900	84600	84800	84900	85900	86300	85900	85600	86300	86700	85500
Total cost of priming	678	718	777	835	897	973	1048	1119	1196	1293	1394	1474
Total COGS	2966	3010	3073	3134	3200	3278	3357	3430	3509	3608	3712	3796
	84900	83900	84600	84800	84900	85900	86300	85900	85600	86300	86700	85500
CASE MEDIUM												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Maintenance people	2288	2292	2296	2299	2303	2304	2307	2311	2313	2316	2319	2321
Business Manager	3432	3438	3442	3448	3452	3456	3462	3468	3474	3480	3484	3489
Electricity for priming GWh/month	0.08	0.09	0.09	0.10	0.11	0.11	0.12	0.13	0.14	0.15	0.16	0.17
Electricity price €/GWh/month	81600	79300	79900	80400	80900	81800	83600	83200	82600	82200	82600	82800
Total cost of priming	6514	6789	7336	7917	8544	9265	10156	10840	11542	12319	13276	14273
Total COGS	12234	12519	13074	13664	14299	15026	15924	16619	17329	18115	19079	20083
	81600	79300	79900	80400	80900	81800	83600	83200	82600	82200	82600	82800
CASE LARGE												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Maintenance people	4576	4585	4595	4602	4611	4614	4619	4622	4626	4631	4634	4643
Business Manager	6864	6871	6880	6891	6906	6915	6926	6934	6946	6961	6976	6990
Electricity for priming GWh/month	0.80	0.86	0.92	0.98	1.06	1.13	1.21	1.30	1.40	1.50	1.61	1.72
Electricity price €/GWh/month	64900	62500	63900	61400	61400	64800	64600	65900	66000	66200	68300	66000
Total cost of priming	51805	53506	58671	60462	64846	73398	78477	85860	92225	99211	109779	113773
Total COGS	63245	64962	70146	71956	76363	84928	90022	97416	103797	110803	121389	125405
	64900	62500	63900	61400	61400	64800	64600	65900	66000	66200	68300	66000

Table B3
Total other costs for each case 2016.

CASE SMALL												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Marketing costs €/month	96	102	109	115	121	112	100	110	146	169	189	205
Maintenance service €/month	200	200	200	200	200	200	200	200	200	200	200	200
Rent, computers, accounting fees, legal fees €/month	500	500	500	500	500	500	500	500	500	500	500	500
Total Other Costs	796	802	809	815	821	812	800	810	846	869	889	905
CASE MEDIUM												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Marketing costs €/month	384	408	434	461	485	448	398	438	584	675	757	819
Maintenance service €/month	800	800	800	800	800	800	800	800	800	800	800	800
Rent, computers, accounting fees, legal fees €/month	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500	1500
Total Other Costs	2684	2708	2734	2761	2785	2748	2698	2738	2884	2975	3057	3119
CASE LARGE												
	2016											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Marketing costs €/month	961	1021	1086	1153	1212	1119	995	1095	1460	1687	1893	2047
Maintenance service €/month	8000	8000	8000	8000	8000	8000	8000	8000	8000	8000	8000	8000
Rent, computers, accounting fees, legal fees €/month	15000	15000	15000	15000	15000	15000	15000	15000	15000	15000	15000	15000
Total Other Costs	23961	24021	24086	24153	24212	24119	23995	24095	24460	24687	24893	25047

Appendix C

.

Table C1
Uncertainties and factor impact on resulting NPV for each scenario (Min, Max, Expected).

				Scenario Min NPV	Scenario Max NPV	Impact +/- of Expected NPV	Impact +/-% of Expected NPV														
General	**Expected value**	**Uncertainty +/-**	**Yearly increase**	**S**	**M**	**L**	**S**	**M**	**L**	**S Min**	**S Max**	**M Min**	**M Max**	**L Min**	**L Max**	**S Min**	**S Max**	**M Min**	**M Max**	**L Min**	**L Max**
Rate of return	15.0 %	3 %	Not applied	-59015	820519	13597517	-36065	1310021	19652434	-10522	12428	-220883	268619	-2731742	3323175	21.70 %	-25.63 %	-21.21 %	25.79 %	-16.73 %	20.35 %
Depreciation plan (years)	10	No impact	No impact																		
Power consumption per rack kWh increase/decrease	0 %	0.5 %	0.5 %	-53643	987591	15720550	-43233	1095621	16934998	-5150	5260	-53812	54219	-608709	605738	10.62 %	-10.85 %	-5.17 %	5.21 %	-3.73 %	3.71 %
Ramp up time (months)	24	20 %	Not applied	-58597	953713	15325577	-41447	1098580	16994899	-10104	7046	-87689	57177	-1003682	665639	20.84 %	-14.53 %	-8.42 %	5.49 %	-6.15 %	4.08 %
Tax rate	22.34%	3 %	Not applied	-50279	987781	15570899	-47278	1097386	17084035	-1786	1215	-53621	55984	-758361	754775	3.68 %	-2.50 %	-5.15 %	5.38 %	-4.64 %	4.62 %
Heat recovery rate	0.97	-0,07 - 0	Not applied	-64337	887959	14588995	-48427	1042461	16329132	-15844	66	-153443	1059	-1740265	-128	32.67 %	-0.14 %	-14.73 %	0.10 %	-10.66 %	0.00 %
Salary employer costs factor	14.4 %	4 %	Not applied	-45676	1032314	16310201	-37807	1052438	16350087	2817	10686	-9088	11036	-19058	20827	-5.81 %	-22.04 %	-0.87 %	1.06 %	-0.12 %	0.13 %
Coefficient of performance (COP)	3.75	25 %	Not applied	-60994	858948	15441535	-30006	1151510	16862352	-12501	18487	-182455	110108	-887725	533093	25.78 %	-38.12 %	-17.52 %	10.57 %	-5.44 %	3.26 %
Salary annual base growth	0.6 %	2 %	Not applied	-51337	1018016	16280605	-33403	1062910	16372797	-2844	15090	-23386	21508	-48654	43537	5.86 %	-31.12 %	-2.25 %	2.07 %	-0.30 %	0.27 %
Maintenance specialist salary €/month	4 000	20 %	Not applied	-50901	1018900	16283146	-32781	1065009	16375588	-2408	15712	-22502	23606	-46114	46328	4.96 %	-32.40 %	-2.16 %	2.27 %	-0.28 %	0.28 %
Business Manager salary €/month	6 000	20 %	Not applied	-55524	1007812	16260392	-27793	1075752	16396949	-7030	20700	-33590	34350	-68868	67689	14.50 %	-42.69 %	-3.23 %	3.30 %	-0.42 %	0.41 %
Heat price €/GWh/month		2 %	2 %	-83118	702388	12934149	-13711	1381201	19724041	-34625	34782	-339014	339799	-3395111	3394781	71.40 %	-71.73 %	-32.55 %	32.63 %	-20.79 %	20.79 %
Electricity price €/GWh/month		2 %	2 %	-61735	917059	15365694	-35493	1167045	17293713	-13242	13000	-124344	125642	-963566	964453	27.31 %	-26.81 %	-11.94 %	12.06 %	-5.90 %	5.91 %
Cases																					
Intial number of racks	10	20 %	Not applied	-52300	1013296	15997518	-45088	1068757	16640600	-3807	3405	-28106	27355	-331742	311341	7.85 %	-7.02 %	-2.70 %	2.63 %	-2.03 %	1.91 %
Maintenance specialist	Case dep.	20 %	Not applied	-50626	1019207	16285596	-32482	1065151	16374679	-2133	16011	-22195	23748	-43664	45419	4.40 %	-33.02 %	-2.13 %	2.28 %	-0.27 %	0.28 %
Business Manager	Case dep.	20 %	Not applied	-55377	1008159	16262017	-28315	1075686	16397773	-6884	20178	-33243	34284	-67242	68513	14.20 %	-41.61 %	-3.19 %	3.29 %	-0.41 %	0.42 %
Marketing costs % of sales	Case dep.	20 %	Not applied	-49510	1038869	16322112	-47818	1043567	16336317	-1017	675	-2533	2165	-7148	7058	2.10 %	-1.39 %	-0.24 %	0.21 %	-0.04 %	0.04 %
Maintenance service €/month	Case dep.	20 %	Not applied	-50676	1033496	16254136	-46840	1048665	16403645	-2183	1653	-7906	7263	-75123	74385	4.50 %	-3.41 %	-0.76 %	0.70 %	-0.46 %	0.46 %
Marginal rent, computers, accounting fees, legal fees	Case dep.	20 %	Not applied	-53853	1028449	16189695	-43438	1056011	16467866	-5360	5055	-12954	14608	-139565	138607	11.05 %	-10.42 %	-1.24 %	1.40 %	-0.85 %	0.85 %
Investment																					
Heat reuse equipment	Case dep.	20 %	Not applied	-50362	1026182	16169003	-46772	1058181	16492288	-1869	1721	-15221	16779	-160256	163028	3.85 %	-3.55 %	-1.46 %	1.61 %	-0.98 %	1.00 %
Connection to DH	Case dep.	20 %	Not applied	-52214	1033749	16259128	-44990	1051049	16402767	-3721	3504	-7653	9647	-70132	73507	7.67 %	-7.22 %	-0.73 %	0.93 %	-0.43 %	0.45 %
Project	Case dep.	20 %	Not applied	-51249	1036246	16302951	-45816	1047492	16357603	-2755	2677	-5156	6090	-26309	28344	5.68 %	-5.52 %	-0.50 %	0.58 %	-0.16 %	0.17 %
Piping	Case dep.	20 %	Not applied	-50487	1037497	16273985	-46976	1047212	16388708	-1994	1517	-3906	5810	-55275	59449	4.11 %	-3.13 %	-0.38 %	0.56 %	-0.34 %	0.36 %
Heat pump	Case dep.	20 %	Not applied	-59677	939838	15424838	-37276	1144482	17232430	-11184	11217	-101564	103079	-904422	903171	23.06 %	-23.13 %	-9.75 %	9.90 %	-5.54 %	5.53 %
										Total Aggregated Uncertainty				**322 %**	**-458 %**	**-148 %**	**130 %**	**-87 %**	**75 %**		

Uncertainty absolute value
Uncertainty from factor
No impact
Most significant factors

Table C2
Monte Carlo simulation input parameters and simulated factors with ranges.

Generic Fixed Parameters	Value				
Number of years	10				
Heat recovery rate	0.97				
Power consumption per rack	0.4286				
Employer cost factor	0.144				
Avg. Maintenance specialist yearly salary / 2	26058				
Avg. Business manager yearly salary / 2	38934				
Depreciation years	10				
Tax rate	0.2234				
Maintenance yearly cost (base case)	9600				
Rent and others (base case)	18000				
Case Related Fixed Parameters	**Value**				
Staff related multiplier Small	0.4				
Staff related multiplier Medium	1				
Staff related multiplier Large	2				
Maintenance related multiplier Small	0.25				
Maintenance related multiplier Medium	1				
Maintenance related multiplier Large	10				
Marketing related multiplier Small	0.05				
Marketing related multiplier Medium	0.02				
Marketing related multiplier Large	0.005				
Total investment related multiplier Small	0.148				
Total investment related multiplier Medium	1				
Total investment related multiplier Large	9.510				
Avg. elec. price related multiplier Small	1.025				
Avg. elec. price related multiplier Medium	1				
Avg. elec. price related multiplier Large	0.773				
Rent and others related multiplier Small	0.333				
Rent and others related multiplier Medium	1				
Rent and others related multiplier Large	10				
Avg. number of racks Small	45				
Avg. number of racks Medium	450				
Avg. number of racks Large	4500				
Simulated Parameters	**Base**	**Min**	**Max**	**Step**	**Number of values**
Heat price	45 900	36 720	55 080	10	1836
Electricity price	80 638	64 510	96 766	10	3225
Total investment	1	0.8	1.2	0.01	40
COP	3.75	2.8125	4.6875	0.1	18
Rate of return	0.15	0.12	0.18	0.001	60
Total permutations	255791520000				

Appendix D

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Table D1
Net present value with Expected input variables.

CASE SMALL	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Total Revenue	0	31460	72866	104460	104460	104460	104460	104460	104460	104460	104460
COGS	0	40074	56093	68673	68926	69139	69410	69639	69900	70177	70504
Gross Profit	0	−8614	16773	35787	35534	35321	35050	34822	34560	34284	33957
Other Cost	0	9973	12043	8400	8400	8400	8400	8400	8400	8400	8400
EBITDA	0	−18587	4730	27387	27134	26921	26650	26422	26160	25884	25557
Depreciation/Amortization	0	11500	11500	11500	11500	11500	11500	11500	11500	11500	11500
EBIT (Small)	0	−30087	−6770	15887	15634	15421	15150	14922	14660	14384	14057
Taxes	0			3549	3493	3445	3385	3333	3275	3213	3140
Net Operating Profit after Taxes	0	−30087	−6770	12338	12141	11976	11766	11588	11385	11170	10916
Depreciation	0	11500	11500	11500	11500	11500	11500	11500	11500	11500	11500
Capital investment	115000										
Operational free cash flow	−115000	−18587	4730	23838	23641	23476	23266	23088	22885	22670	22416
Present value (Small)	−115000	−16163	3576	15674	13517	11672	10058	8680	7481	6444	5541
Net Present Value (Small)	−48519										
Return on investment (ROI)	49 %										
CASE MEDIUM											
Income Statement	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
Total Revenue	0	314600	728661	1044601	1044601	1044601	1044601	1044601	1044601	1044601	1044601
COGS	0	187966	339730	461292	461078	461022	461394	461996	462265	461717	461500
Gross Profit	0	126633	388931	583309	583523	583579	583208	582605	582337	582884	583101
Other Cost	0	33892	42173	27600	27600	27600	27600	27600	27600	27600	27600
EBITDA	0	92741	346758	555709	555923	555979	555608	555005	554737	555284	555501
Depreciation/Amortization	0	77500	77500	77500	77500	77500	77500	77500	77500	77500	77500
EBIT (Medium)	0	15241	269258	478209	478423	478479	478108	477505	477237	477784	478001
Taxes	0		60152	106832	106880	106892	106809	106675	106615	106737	106785
Net Operating Profit after Taxes	0	15241	209106	371377	371543	371587	371298	370831	370622	371047	371216
Depreciation	0	77500	77500	77500	77500	77500	77500	77500	77500	77500	77500
Capital investment	775,000										
Operational free cash flow	−775000	92741	286606	448877	449043	449087	448798	448331	448122	448547	448716
Present value (Medium)	−775000	80644	216715	295144	256742	223275	194028	168544	146492	127505	110916
Net Present Value (Medium)	1045006										
Return on investment (ROI)	412 %										
CASE LARGE											
Income Statement	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
Total Revenue	0	3145995	7286613	10446014	10446014	10446014	10446014	10446014	10446014	10446014	10446014
COGS	0	1080432	2311878	3272991	3226634	3180346	3133960	3087937	3041943	2995979	2949930
Gross Profit	0	2065563	4974734	7173023	7219380	7265668	7312053	7358077	7404070	7450035	7496083
Other Cost	0	291730	312433	276000	276000	276000	276000	276000	276000	276000	276000
EBITDA	0	1773833	4662301	6897023	6943380	6989668	7036053	7082077	7128070	7174035	7220083
Depreciation/Amortization	0	737000	737000	737000	737000	737000	737000	737000	737000	737000	737000
EBIT (Large)	0	1036833	3925301	6160023	6206380	6252668	6299053	6345077	6391070	6437035	6483083
Taxes	0	231628	876912	1376149	1386505	1396846	1407209	1417490	1427765	1438034	1448321
Net Operating Profit after Taxes	0	805204	3048389	4783874	4819875	4855822	4891845	4927587	4963305	4999001	5034763
Depreciation	0	737000	737000	737000	737000	737000	737000	737000	737000	737000	737000
Capital investment	4125000	3245000									
Operational free cash flow	−4125000	−1702796	3785389	5520874	5556875	5592822	5628845	5664587	5700305	5736001	5771763
Present value (Large)	−4125000	−1480692	2862298	3630064	3177161	2780621	2433505	2129528	1863440	1630530	1426691
Net Present Value (Large)	16328146										
Return on investment (ROI)	1046 %										

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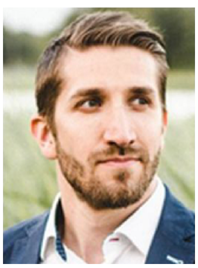

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