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Modeling Storage and Demand Management in Electricity Distribution Grids

Andreas Schroeder [a], Jan Siegmeier [b], Murk Creusen [b]

Abstract:
Storage devices and demand control may constitute beneficial tools to optimize electricity generation with a large share of intermittent resources through inter-temporal substitution of load. We quantify the related cost reductions in a simulation model of a simplified stylized medium-voltage grid (10kV) under uncertain demand and wind output. Benders Decomposition Method is applied to create a two-stage stochastic program. The model informs an optimal investment sizing decision as regards specific 'smart grid' applications such as storage facilities and meters enabling load control. Model results indicate that central storage facilities are a more promising option for generation cost reductions as compared to demand management. Grid extensions are not appropriate in any of our scenarios. A sensitivity analysis is applied with respect to the market penetration of uncoordinated Plug-In Electric Vehicles which are found to strongly encourage investment into load control equipment for `smart` charging and slightly improve the case for central storage devices.

Keywords: Storage, demand management, stochastic optimization, Benders Decomposition

JEL: Q40, Q41

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1. Introduction

Since electricity demand and the availability of output from Renewable Energy Sources (RES) are intermittent by nature, system operators have to resort to relatively costly measures such as reserve energy to maintain system stability. In the coming decade, back-up capacities are set to become more relevant with increasing shares of RES penetration. In this context, storage devices serve to store excessive electricity generation and feed-in missing energy in times of need. An alternative concept of better aligning demand and supply of electricity through two-way digital communication technology is commonly referred to as 'smart metering'. Measures to manage demand with the help of smart meters include demand response and direct load control. Our work emphasises the latter.

The purpose of this paper is to demonstrate how stochastic optimization and Benders decomposition method can be sensibly applied to analyze and compare investment options in a power distribution system setting. We scrutinize load control and storage facilities as potential options targeting at electricity generation cost reductions. With this common purpose, direct load control and centralised storage are two competing or possibly complementary solutions from the perspective of a power distribution system operator. Besides, we test whether conventional grid reinforcements could alleviate the need for storage and load control. The idea is that storage and DSM may be used to avoid capacity shortages. If so, avoided shortage adds value to storage or DSM devices because of capacity upgrade deferral (Pudjianto et al., 2006).

There exists a broad range of literature dealing with storage sizing decisions. Some of these studies perform numerical optimizations in a deterministic setting (Diaf et al., 2007; Arun et al., 2008). Applications of stochastic patterns of generation and demand can be found in Ekren et al. (2009), Ekren an Ekren (2009, 2010) and Tan et al. (2010). Tan et al. (2010) present a stochastic optimization model of battery sizing for demand management with emphasis on outage probabilities which is not dealt with in this paper. Roy et al. (2010) apply stochastic wind generation patterns to a wind-battery system sizing model with deterministic demand. IEA (2010) do likewise with Plug-in Electric Vehicles (EV) as storage facilities.

Concerning demand-side management (DSM), we found no research publications to focus on investment decisions into DSM appliances from the perspective of a distribution system operator. Manfren et al. (2011) focus on distributed generation planning but abstract from any investment analysis. Ki Lee et al. (2007) assess investment into demand management systems for heating in a national case study for Korea. Neenan and Hemphill (2008) investigate investment from a societal perspective while Strbac (2008) and Electricity Journal (2008) found that investment into DSM appliances might not be all that profitable in general. We intend to further investigate this claim in our analysis.

Our contribution is unique in so far as no study has explicitly compared the cost saving potential of storage and DSM in a comprehensive model including grid representation, endogenous investment and factors of uncertainty. No study known to the authors has combined a cost-benefit analysis of 'smart' technologies with a distribution network representation and considerations of stochastic demand and production. Whilst an 11kV distribution network representation in combination with a benefit analysis for storage and demand response measures can be found in Wade et al. (2010), the present work complements Wade et al.'s analysis by adding endogeneity to the investment into storage devices and DSM appliances as well as uncertainty of demand and wind generation. Furthermore, one of our contributions to the research area consists in the application of Benders Decomposition Method to the stochastic program. Decomposition methods have been applied to numerous Operations Research topics in the energy sector, such as unit-commitment (Niknam, 2009). To our knowledge, though, there exists no application to evaluating storage and DSM infrastructure investment as done in this work.

The article is divided into a descriptive part, including the methodology and model description, an explanation of parameters and scenarios applied. Subsequently, results are outlined, discussed and final conclusions are drawn.

2. Model Description

We apply a basic direct current (DC) flow model adapted to a situation with DSM and storage technologies in a stylized 10 kV medium-voltage grid representative for Germany. The model is designed as linear program under a cost minimization regime with hourly time resolution of two exemplary holidays (winter/summer). A vertically integrated system operator is considered as the cost minimizing agent. As explicated before, the aim of the operator is to reduce generation cost by performing load management through storage and DSM. He can decide on whether to invest into storage and DSM technology and on how to operate it. We assume a perfectly inelastic, hence vertical demand function. This is a suitable approach here, since we focus on the producer side. There is no demand response. Still, the operator is able to shift the vertical demand curve left and rightwards through direct load control. Thus, our extensive-form cost-minimisation objective reads as follows.

$$\min_{\substack{\{DSM\_inv_n\}\{S_n^{cap\max}\}\{DSM_{n,t,sc}\} \\ \{SIN_{n,t,sc}\}\{G_{s,n,t,sc}\}\{SOUT_{n,t,sc}\}\{\Delta_{n,t,sc}\}}} \sum_{sc=1}^{SC}\sum_{n=1}^{N}\sum_{t=1}^{T}\left[prob_{sc}\cdot\sum_{s} c_s \cdot \sum_{s} G_{s,n,t,sc}\right] + \sum_{n=1}^{N}\left[DSM\_INV_n \cdot dsm\_c + S_n^{cap\max}\cdot s\_c\right]$$

The agent minimizes generation cost $c_s \cdot G_{s,n,t,sc}$ of each technology s as well as investment cost of DSM $DSM\_INV_n \cdot dsm\_c$ and storage $S_n^{capmax} \cdot s\_c$. Besides generation and investment, he can manipulate storage in- and outflow ($SIN_{n,t,sc}$ and $SOUT_{n,t,sc}$), shed or induce consumption ($DSM_{n,t,sc}$) and transfer electricity from one node to another ($\Delta_{n,t,sc}$), subject to constraints detailed below. Sets, parameters and variables are further specified in Table 1.

Set	Description	Unit	Range
I	Node	-	N={0,...,5}
T	time period (summer / winter)	H	T={1,...,24}
S	generation technology	-	9
L	Line	-	4 lines
SC	Scenario	-	50 scenarios
Variable	**Description**	**Unit**	**Range**
$DSM_{n.t.sc}$	demand-side-management	kWh	Free
$SIN_{n.t.sc}$	storage inflow	kWh	Positive
$SOUT_{n.t.sc}$	storage outflow	kWh	Positive
$G_{s.n..t.sc}$	Generation	kWh	Positive
DSM_INV_n	DSM investment	Consumer	0-360
S_n^{capmax}	storage capacity investment	kWh	Positive

$\Delta_{t.n.sc}$	phase angle difference (choose Δ_1=0)	-	free
Parameter	**Description**	**Unit**	**Range**
$Q_{n.t.sc}$	Total demand including DSM and storage	kWh	Positive
$q^{ref}_{n.t.sc}$	Demand	kWh	Positive
$prob_{sc}$	probability of scenario SC	%	0 – 100
c_s	variable generation cost (acc. to merit	EUR/kWh	0.001 - 0.07
dsm_c	DSM investment cost	EUR/kWh	Positive
s_c	storage investment cost	EUR/kWh	Positive
H	storage efficiency (zero leakage from	%	75
$dsm_{t.n}^{posmax}$	positive load shift capacity	kWh	cf. Annex
$dsm_{t.n.}^{negmax}$	negative load shift capacity	kWh	cf. Annex
$lf_{l.t.sc}$	electricity flow	kW	see lf_l^{max}
$B_{l.n}$	network susceptance matrix	1/Ω	see x
$H_{l.n}$	weighted network matrix	1/Ω	see x
$ln_{l.n.sc}$	incidence matrix	1	0 or 1
lf_l^{max}	maximal capacity for line flow	kW	1850
$slack_n$	slack variable (with $slack_1$=1)	1	0 or 1
X	reactance of line	1/Ohm	0.4 - 0.5

Table 1: Sets, variables and parameters used.

On the demand side, consumers are aggregated at each of the 10kV/0.4kV sub-station nodes *n*. Thus, a diurnal pattern of consumer demand (without DSM and storage), denoted by $q^{ref}_{n,t,sc} \geq 0$, can be approximated using standard averaged load profiles weighted by the number of customers at the respective node.

Putting demand, supply and network flows together, the energy balance constraint per node reads:

1) total demand $$Q_{n,t,sc} = q^{ref}_{n,t,sc} + DSM_{n,t,sc} + SIN_{n,t,sc} \quad ,$$

2) Energy balance : $$\sum_s G_{s,n,t,sc} + SOUT_{n,t,sc} - Q_{n,t,sc} - \sum_m b_{m,n}\Delta_{m,t,sc} = 0 \quad (\forall n,t,sc)$$

This incorporates the simultaneity of generation and consumption as well as the first Kirchhoff rule. The consumer demand $q^{ref}_{n,t,sc}$ is supplemented by contributions from DSM and charging of a battery to yield total demand $Q_{n,t,sc}$, as specified in equation 1.

On the supply side, we consider a setup where each generation technology $s \in S$ at time $t \in T$ and node $n \in N$ contributes an amount $g_{s,n,t,sc}$ to total electricity generation at marginal unit cost c_s, up to its capacity limit $G^{max}_{s,n,t,}$ which is exogenous and time-dependent.

3) Generation limit : $$g^{\max}_{s,n,t} - G_{s,n,t,sc} \geq 0 \quad (\forall n,s,t,sc)$$

A number of grid-related constraints are included to study the grid impact of storage and DSM operation. The topology of a lossless DC network with *L* lines is described by the *L x N* network adjacency matrix *ln*, where $ln_{l,n} = 1$ means that line $l \in L$ starts at node *n*, while $ln_{l,m} = -1$ means that it ends at node *m*. Weighting each line with the inverse of its reactance x_l, we obtain the matrix *h* (equ. 4.1) and thus the network susceptance matrix *B* (equ. 4.2). If the phase angle of node n at time t is denoted by $\Delta_{n,t}$, the flow along line l at time t is given by equation 4.3, where the sign of $lf_{l,t}$ depends on the direction of the flow. Since $\Delta_{n,t,sc}$ is defined relative to a reference bus, slackness conditions $slack_n \, \Delta_{n,,t,sc} = 0$ hold, and we choose $slack_1 = 1$ (that is, $\Delta_{1,t,sc} = 0$) to set node 1 as the reference node (equ. 4.5). Equation 4.4 represents the physical constraints of the lines (in a DC network, only the thermal limit is relevant).

4.1) weighted netw. matrix : $$h_{\mathrm{l,n,sc}} = \frac{1}{x_l} \ln_{l,n,sc}$$

4.2) Network susceptance : $$b_{n,m} = \sum_{sc} \sum_{l} h_{l,n,sc} \ln_{l,m,sc} \quad (\forall n)$$

4.3) line flow : $$lf_{l,t,sc} = \sum_{n} h_{l,n}, sc\Delta_{n,sc,t} \quad (\forall l,t,sc)$$

4.4) line flow limits : $$-lf_l^{\max} \le lf_{l,t,sc} \le lf_l^{\max} \quad (\forall l,t,sc)$$

4.5) flow convention : $$slack_n \Delta_{t,sc}^n = 0 \quad (\forall n,t,sc), \quad slack_1 = 1$$

The second set of constraints relates to DSM. When direct load control is made possible, electricity consumption may be shifted to earlier or later stages if exact timing is not crucial. This is done by the system operator with the aim of saving cost. The option for DSM is reflected in an additional contribution to total demand, $DSM_{n,t,sc}$. Reducing and increasing demand is possible up to limits $dsm_{t,n}^{neg,max}$ and $dsm_{t,n}^{pos,max}$, respectively (equ. 5.1). Note that both parameters are defined as positive numbers while contributions have to balance to zero over time (equ. 5.2).

Likewise, storage facilities in the distribution network can take up a positive charge $SIN_{n,t,sc}$ at time t, convert it (with some loss η) and subsequently provide positive amounts $SOUT_{n,t,sc}$, where the overall balance is also governed by capacity constraints (equ. 6.2) as well as input and output kW power constraints, which are set equal to kWh capacity constraints for reasons of simplicity (equ. 6.3). Note that we set energy capacity equal to power limit and that there is no continuation value of left-over storage since the storage device is empty at the last time period (equ. 6.1).

5.1) DSM limits : $$-d_{n,t}^{neg,\max} \cdot DSM\_INV_n \le DSM_{n,t,sc}, \quad DSM_{n,t,sc} \le d_{n,t}^{pos,\max} \cdot DSM\_INV_n \quad (\forall n,t,sc)$$

5.2) const. total demand : $$\sum_{\mathrm{sc}} \sum_{t=1}^{T} DSM_{n,t,sc} = 0 \quad (\forall n)$$

6.1) storage balance : $$\sum_{t=1}^{T} \left(SIN_{n,t,sc}\eta - SOUT_{n,t,sc} \right) = 0 \quad (\forall n,sc)$$

6.2) Storage capacity limits : $$\sum_{\tau=1}^{t} SOUT_{n,\tau,sc} - \sum_{\tau=1}^{t-1} SIN_{n,\tau,sc}\,\eta \le 0, \quad \sum_{\tau=1}^{t} SIN_{n,\tau,sc}\,\eta - \sum_{\tau=1}^{t-1} SOUT_{n,\tau,sc} - S_n^{cap,\max} \le 0 \quad (\forall n,t,sc)$$

6.3) Storage power limits : $$S_n^{cap\max} - SOUT_{n,t,sc} \ge 0 \quad , \quad S_n^{cap\max} - SIN_{n,t,sc} \ge 0 \quad (\forall n,s,t,sc)$$

7) non - negativity : $$G_{s,n,t,sc} \ge 0, \quad SOUT_{n,t,sc} \ge 0, \quad SIN_{n,t,sc} \ge 0 \quad (\forall n,s,t,sc)$$

The problem is formulated as two-stage stochastic optimization program, with initial investment at the first stage and operative optimizations at the second stage, cf. Figure 1. We apply Benders Decomposition Method (Birge and Louveaux, 1997) with conflicting variables being initial investment levels into storage and DSM. The first-stage (master) and the second-stage (recursive sub-problem) are successively solved in loops until convergence of the upper and lower level objective is reached. In our case, the sub-problem objective represents the upper bound as a restriction of the initial problem and the master problem yields a lower bound as a relaxation of the initial problem. The solution algorithm stops if the difference between the minimum upper bound and the current lower bound is less or equal to a very small number. Otherwise the algorithm continues. Benders optimality cuts are added to the problem set of constraints after each iteration. Moreover, feasibility cuts ensure that infeasibilities in the sub-problem due to misallocations in the master problem are ruled out, cf. Figure 1. The Benders approach reduces computation effort as compared to solving the extensive form expected-value-problem. The relaxed master problem objective function now reads:

$$\min_{\{DSM\_INV_n\}\{S_n^{cap\max}\}} \sum_{n=1}^{N} \left[DSM\_INV_n \cdot dsm\_c + S_n^{cap\max} \cdot s\_c \right] + \alpha$$

Here, α is the objective value of the sub-problem. The recursive sub-problem objective function becomes:

$$\min_{\{DSM_{n,t,sc}\}\{SIN_{n,t,sc}\}\{G_{s,n,t,sc}\}\{SOUT_{n,t,sc}\}\{\Delta_{n,t,sc}\}} \sum_{sc=1}^{SC} \sum_{\mathrm{n}=1}^{N} \sum_{t=1}^{T} \left[prob_{sc} \cdot \sum_{s} c_s \cdot \sum_{s} G_{s,n,t,sc} \right]$$

The execution of the presented model requires the creation of appropriate scenarios regarding the stochastic parameters determining demand and wind production. A random sampling method is utilized for the simulation of realizations, cf. Figure 1. Random sampling techniques are popular in risk analysis and have been used in previous research on electricity topics (Tan et al., 2010, Roy et al., 2010). We obtain a range of demand and wind profiles and assign a uniform probability distribution to the occurrence of each scenario. Subsequently, we implement a numerical optimization model in the software package General Algebraic Modeling System (GAMS).

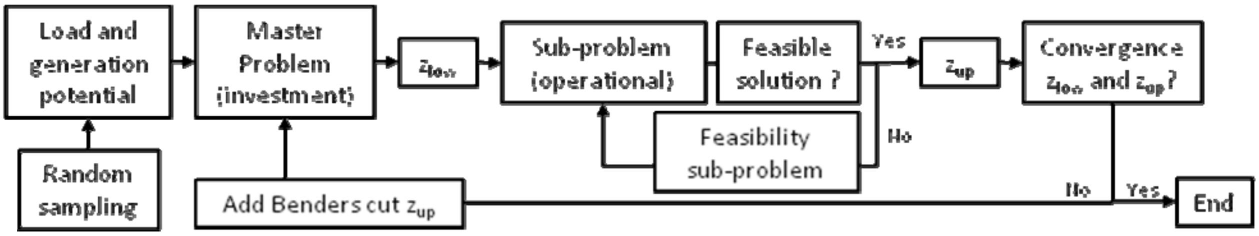

Figure 1: Algorithm used for solving the two-stage problem. (*Source: Own illustration*)

4. Input Parameters

4.1 Demand

In our stylized system, demand occurs at demand nodes which are connected to individual households and commercial units. Specific demand profiles are denoted $q^{ref}_{n,t,sc}$. Demand is treated stochastically under the assumption of zero correlation between wind availability and demand. Simulated demand values (cf. Figure 2) are drawn from a normal probability distribution with time-varying mean and standard deviation. Standard deviations of demand variability are based on empirical demand realizations at the EEX wholesale intraday market (2010). Deriving medium-voltage demand variability from wholesale market demand fluctuations is reasonable for model systems with aggregation of a high number of consumers. Note that the more consumers are aggregated, the less volatile is energy consumption (cf. Widen and Wäckelgard, 2010).

The model incorporates electricity consumption of EV into the stochastic reference demand $q^{ref}_{n,t,sc}$. A load pattern is assumed with 8 hours home charging time at a rate of 1.6 kW, cf.

Figure 3. 1.6kW is a relatively slow, usually referred to as Level 1 charging. A 12.8 kWh charge per night corresponds to a ca. 100 km range. Note that EV are not equivalent to storage facilities in our model. This implies we do not consider any vehicle-to-grid technology. Uncontrolled EV solely behave as an additional consumer whose load can be curtailed and shifted if DSM appliances are installed. Charging behaviour is under full control of the system operator if the EV is connected to a smart meter. Different penetration rates of EV are tested from zero to 10%, that is zero to 10% of the consumers own an EV.

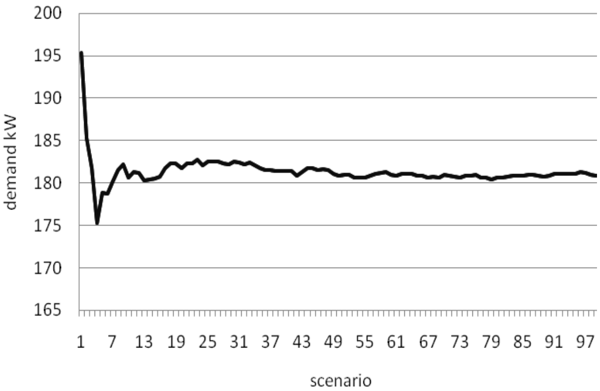

Figure 2: Convergence of sample demand mean with an increasing amount of scenarios. *(Source: Own production)*

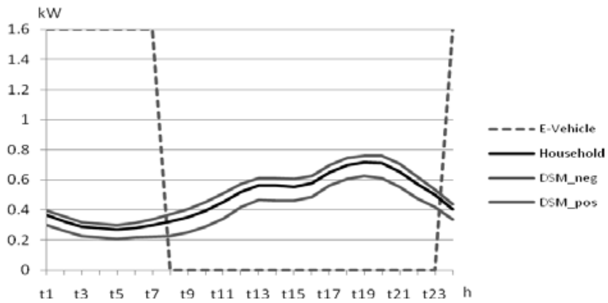

Figure 3: Deterministic standard load profile with corridor for upper and lower bounds of the DSM potential on a winter holiday. Additionally, the graph plots one EV charging profile. (*Sources: Own production based on BDEW (2010), Grein et al. (2009), Stadler (2008)*)

We assume 360 consumers per 10kV-0.4kV transformer. Each consumer unit is equivalent to a 1.99-person household, a representative mix for Germany (Prognos et al., 2010). The share of commerce and households is 21% and 79% in the model. We abstract from the industrial sector in our model because – by law - industrial consumers are already equipped with appliances for DSM when yearly consumption exceeds 100,000 kWh.

4.2 Load control

Investments in load control infrastructure for DSM have the benefit of allowing inter-temporal shifts of electricity demand. This may yield peak load reductions and imply infrastructure reinforcement deferral. However, we disregard that the installation of DSM appliances could yield overall demand reductions. We do this not only because projections of demand reduction through DSM devices appear to be fairly uncertain and consumer-specific, ranging between zero and 20% (Moura and Almeidaa, 2010 versus Papagiannis et al., 2008, EcoFys, 2009). Our focus lies on direct load control exerted by the system operator. Demand response measures and related consumption savings driven by consumer behaviour are beyond the scope of this operator´s cost-minimization model.

Once appliances for DSM are rolled out, there is a certain time-dependent limit on the load shifting potential. Positive and negative shifts are possible and their potential is asymmetric. $D^{neg,max}_{n,t}$ represents the amount of energy that can be saved at each time by shifting load away to another period of the day. Accordingly, the $D^{pos,max}_{n,t}$ curve shows the potential load that can be added at each time. The potential to increase energy load at each time, $D^{pos,max}_{n,t}$, is generally larger than $D^{neg,max}_{n,t}$. The DSM potential for average households and commerce is calculated using numbers from a study report for the city of Mannheim, Germany, (Grein et al., 2009) and triangulated with Stadler (2008). EV availability is added to the DSM potential. The resulting potential can be observed for each time slice in Figure 3 and Figure 8. Figure 3 plots an average load profile for a household with the corridor of maximum and minimum load when DSM appliances are installed.

The total cost of equipment for DSM currently figures in between 160 and 350 EUR per installed system (EcoFys, 2009). We refer to the Advanced Metering System (AMM), which includes two-way communication via an integrated router gateway per house. This system enables time-of-use pricing and direct load control up to the capacities detailed in Figure 8. The cost figure includes investment into hardware such as meter, gateway, router and its initial installation. In order to calculate lifetime cost, we apply a 6.5% annual discount rate with a lifetime of 16 years (EcoFys, 2009).

4.3 Storage

The model considers investment into a central large-scale stationary battery with endogenous capacity and conversion efficiency factor 75%. We focus on batteries instead of mechanical conversion systems (pumped hydro, compressed air storage) for batteries require little up-front installation cost. To account for different battery technologies, we vary the cost input data. Approximated cost data of equipment and installation is compiled in Table 2 for reference. In our cost considerations, we assume a life-time of 3,000 cycles at 80% depth of discharge with one cycle being completed every three days, hence a life-time of ca. 12 years. To facilitate tractability and increase computation speed, the three dimensioning vectors of a storage unit – capacity in kWh, charge rate and discharge rate in kW - are all set equal in this analysis. We believe this assumption to be justifiable in a setting with hourly time resolution where ramping constraints and thus power limits are of secondary importance in contrast to capacity limits. In the real world, actual batteries often feature power limits even higher than energy capacity limit. This holds true notably for storage devices that serve as reserve for capacity markets.

Conversion	Storage type	EUR/kWh	EUR/kW	Cycles (100%)	Efficiency
Mechanical	Supercapacitor	3,800-4,000	100-400	10,000-100,000	95-100 %
	Flywheels	1,000-3,000	300	20,000-60,000	90-95 %
	Pumped Hydro	60-150	500	20,000-50,000	70-85 %
	Compressed Air	30-120	550	9,000-20,000	70–80 %
Electro-chemical	Nickel-metal hydride	700-800	-	500-3,000	65 %
	Nickel-Cadmium	350-800	175	1,000-3,000	60-70 %
	Sodium-Sulfur	200-900	150	2,000-3,000	85-90 %
	Lithium-Ion	200-500	175	3,000-6,000	95-100 %
	Vanadium Redox-Flow	100-1,000	175	2,000-3,000	75-85 %
	Zinc-Bromine	50-400	175	> 2,000	70 %
	Lead Acid	50-300	175	200-1,100	75 %

Table 2: Current storage investment cost data compiled from various sources. Mechanical bulk storage included for reference but not considered in our calculations. (*Sources: EcoFys (2009), Schoenung and Eyer (2008), and Electricity Storage Association (2011)*)

4.4 Grid

Investment decisions relating to DSM and storage should ideally consider grid infrastructure constraints because load shifting may serve as a mean to avoid capacity shortage and system outage probability. This can be notably relevant in grids with relatively disadvantageous topology (series connection). Pudjianto et al. (2006) explicitly take into account this "delaying capacity replacement" value of DSM devices when appraising the worthiness of DSM. In the absence of real-world data of medium-voltage grids, we decide to simulate a stylized configuration with characteristics that approximate realistic grids, cf. Figure 4 (Fletcher and Strunz, 2007).

The grid representation used in this study consists of five nodes, one of them the grid supply point (GSP) and additionally demand nodes with 10kV/400V transformers. The nodes are connected in line so as to simulate a ‘worst-case’ topology, cf. Figure 4. The analysis restrains to the 10kV-level of a stylized distribution network. An application of the presented DC flow model to a 400V level is delicate for the DC load model does not include reactive power. At 400V level, voltage drop limits and reactive power are of high relevance. Large-scale generation, including wind turbines and pump storage are assumed to be connected at the 10kV level, whilst DG and EV are part of the underlying 400V grid. 10kV overhead lines have a lateral surface of 70mm^2 with associated capacity of 185 Ampere. In a 10 kV DC setting this results in a maximum capacity limit of 1,850 kW. A typical reactance of the 10kV network is around 0.4 Ohm/km (Pudjianto et al., 2006; Fletcher and Strunz, 2007). Upgrade costs of overhead circuits in a comparable 11 kV grid lie at 3,102 €/MW/km (Pudjianto et al., 2006). We assume all lines to be 2 km long and line flows do not incur transmission losses.

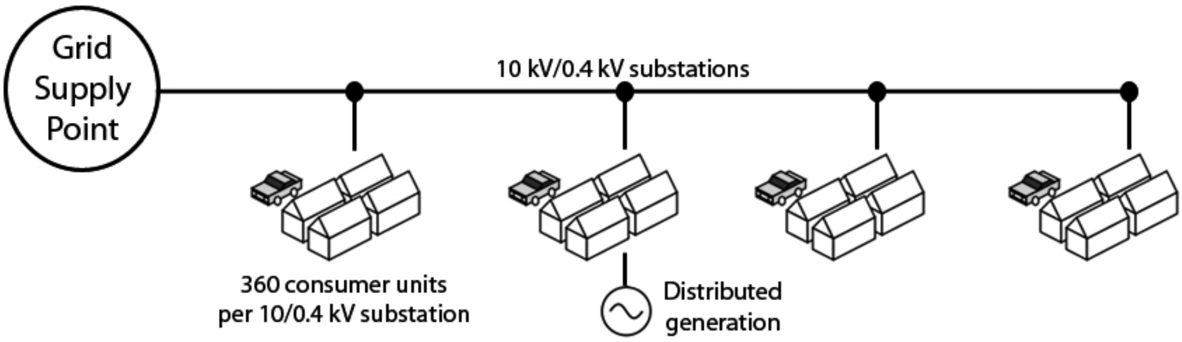

Figure 4: Stylized 5-node distribution grid configuration in series connection. (*Source: own illustration*).

4.5 Generation

Nine technologies are part of the generation mix in this work: Six technologies – hydro, nuclear, lignite, hard coal, gas and biomass – have flexible generation capacities with full availability and flexibility at any time (up to a technical factor, e.g. due to maintenance requirements, taken from Prognos et al. (2010)). Three technologies have varying availability. Small-scale heat-controlled CHP diurnal patterns follow an approximation in Pudjianto et al. (2006) for both winter and summer and they are weighted by a seasonal factor based on data in Brunnengräber et al. (1996) to account for higher heating demand (and thus more electricity supply) during winter. Likewise, photovoltaic power (PV) exposes different daily profiles by season adapted to a Northern German location (Solar-Wetter, 2010).

Investment decisions into storage and DSM consider a long time frame and confront with uncertainty about the future generation technology mix. Whilst an investment appraisal should consider today’s investment cost, generation cost reductions accrue in the uncertain future and should therefore be estimated accordingly. A sophisticated dynamic investment model could explicitly model the evolution of the generation park over time. Such long-term approach is beyond the scope of this paper, though. We believe the year 2020 to be a reasonable representative ‘average’ year regarding the penetration of renewable energy resources over the life-time of a storage or DSM investment these days. Therefore, a hypothetical generation limit of each generation technology is derived from a forecast for the year 2020 given in Prognos et al. (2010). We scale down the available installed capacity in Germany so that the six base load technologies match the maximum demand in our model network. This ensures enough power is available at all times, even if the fluctuating sources are not available. Additionally, the three intermittent technologies are each scaled by an individual factor so that the total amount of diurnal maximum energy production matches the projections for 2020 in Prognos et al. (2010).

Finally, we assume that generation capacities are distributed differently between the nodes of our small network – while the bulk of power will be available via the grid supply point, some of the CHP, PV and biomass capacity is located at the demand nodes. These assumptions are summarized in the parameters $G^{max}_{s,t,n}$, specifying the maximum available power from each generation technology per time slot and per node. Incremental generation cost is illustrated in Table 3. The figures are independent from the utilization rate of a generation technology.

Available energy (per day, aggregated over all nodes)											
demand peak [kW]		989.25									
Technology		**Wind**	**PV**	**CHP**	**Biomass**	**hydro**	**nuclear**	**lignite**	**coal**	**gas**	Total
Type	Source	time-dependent	time-dependent	time-dependent	Flexible	flexible	Flexible	flexible	Flexible	flexible	
installed capacity (Germany 2020) [GW]	Prognos et al. (2010)	40.9	33.3	4	5.7	7.7	6.7	22.4	28.5	24.4	173.6
electricity generation (Germany 2020) [TWh]	Prognos et al. (2010)	94	31	20	37	7.5	49.2	145.2	120.2	40.4	544.5
capacity utilization (where relevant)	Calculation	26.2%	10.6%	57.1%							
technical availability (where relevant)	Prognos et al. (2010)				88%	90%	93%	86%	84%	84%	
installed capacity [kW] (in model)	Calculation	483.00	393.25	47.24	92.70	90.93	79.12	264.53	336.56	288.15	2075.48
available energy, per day [kWh] (in model)	Calculation	3041.29	1002.98	647.08	1957.88	1964.11	1766.00	5459.84	6785.12	5809.02	28433.33

Technology	**Wind**	**PV**	**Hydro**	**CHP**	**nuclear**	**lignite**	**coal**	**Gas**	**biomass**
Marginal cost [EUR/kWh]	0.005	0.009	0.005	0.003	0.010	0.04	0.038	0.07	0.016

Table 3: Available capacity and projections of marginal generation cost incl. carbon cost in 2020. *(Sources: Based on Prognos et al. (2010))*

Special attention is given to generation data of wind power which is treated as stochastic parameter. In order to calculate power density - the distribution of wind energy at different average wind speeds - the power of wind speeds is multiplied with the probability of each wind speed, drawn from a Weibull probability distribution with shape parameter 2 (typical for Central Europe) and a scale parameter which varies by time-of-day (Ekren et al., 2009; Roy et al., 2010) and which is calibrated to match a typical on-shore location in Northern Germany. A random sample of wind speeds is created in accordance with the inverse Weibull distribution with *w*, the wind speed in m/s, *x*, a uniform random number between 0 and 1, a scale and a shape parameter:

$$W = \text{scale} \cdot [-\ln(1-x)]^{\frac{1}{\text{shape}}}$$

Knowing that energy potential per second (the power) varies in proportion to the cube of the wind speed (in m/s) it is then possible to calculate actual wind energy production in kWh. The number of wind rotors and their conversion efficiency were calibrated so as to match a share of wind energy in total production conform to projections in Prognos et al. (2010). Cut-in, rated and cut-out wind speeds are assumed to figure at 2.8 m/s and 16.5 m/s respectively whilst rated wind speed ends at 7 m/s, cf. Figure 5 (Roy et al., 2010).

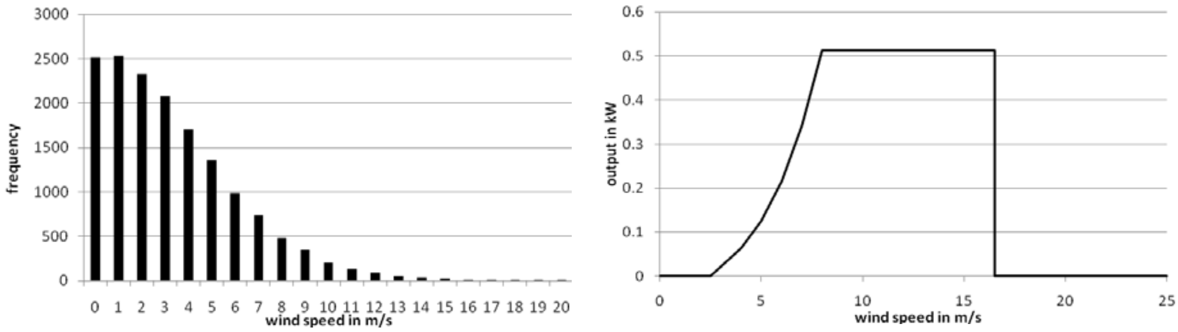

Figure 5: Frequency of wind speeds with average wind speed 5.22 m/s at specified cut-in and cut-out rates. (*Source: Own production based on Roy et al. (2010)*)

5. Results

The linear problem is implemented in GAMS, using the solver CPLEX 9.0 with standard options. Our 1.3 GHz CPU machine executes the stochastic linear program for one exemplary day in between 2 and 8 minutes time, depending on cost parameter values. Up to 20 iterations are needed. The deterministic model is solved within a few seconds time.

As shown in Figure 6, we find storage devices to pay off at investment cost below 900 EUR/kWh of capacity. For instance, if costs amount to 300 EUR/kWh, storage devices are profitable up to a size of roughly 0.5 MWh capacity (and MW power limit) in the framework of our model, depending on the degree of EV penetration. That corresponds to ca. one fourth of installed generation capacity (2.075 MW) and one half of peak demand (ca. 0.989 MW) in the system. In total, we find that less than 1 % of aggregated electricity consumption is stored in most scenarios, cf. Figure 7. A higher number of EV, hence additional load, further improves the case for storage devices. Given these numbers, it can be concluded that even relatively expensive technologies such as Nickel-Cadmium and Nickel-metal hydride batteries seem to be profitable in medium-voltage grids of our type. In contrast, super-capacitors and flywheels need to severely cut their cost in order to become competitive. Current investment cost lies between 2,000 and 4,000 EUR/kWh.

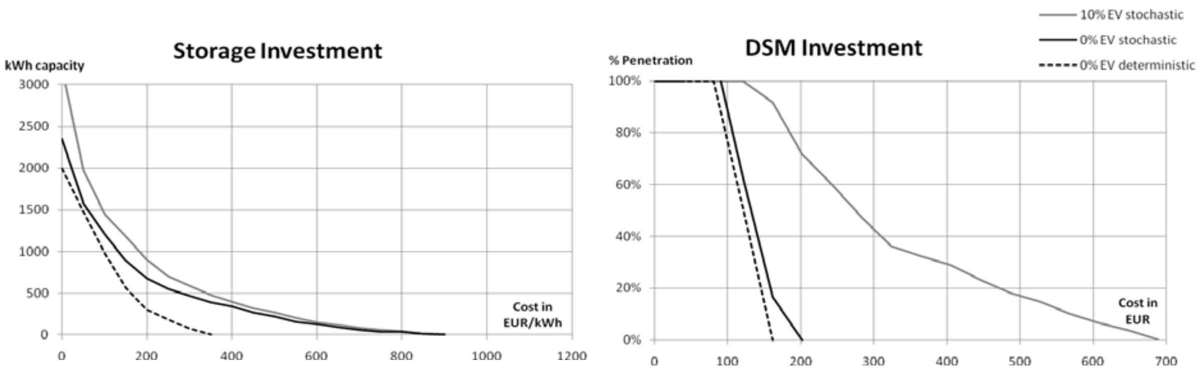

Figure 6: Investment into storage and DSM under varying investment cost and penetration degree of electric vehicles. The dotted line corresponds to results of the deterministic model. Curves are interpolated from several mode runs. (*Source: Own production*)

Appliances for DSM prove hardly profitable in the deterministic model setting, which echoes a finding of Strbac (2008) and Electricity Journal (2008). Likewise, the stochastic model predicts DSM to be little beneficial in the absence of EV. Only if all-inclusive investment costs boil down to 200 EUR per consumer, investment into load control technology may become beneficial. Note that current costs for AMM systems lie at 260 EUR in average and projections for 2020 figure at around 160 EUR minimum (EcoFys, 2009). The break-even point (tolerance threshold) for investment into DSM increases to 700 EUR when 10% of consumers own electric vehicles. Such strong shift clearly outlines that a high number of EV induces investment into load control equipment. When in competition to each other at current cost, investment into storage devices is thus clearly favored to DSM systems. This effect is minimal or partly reversed when EV penetration is high. Obviously, storage devices offer more flexibility to load shifting than does DSM.

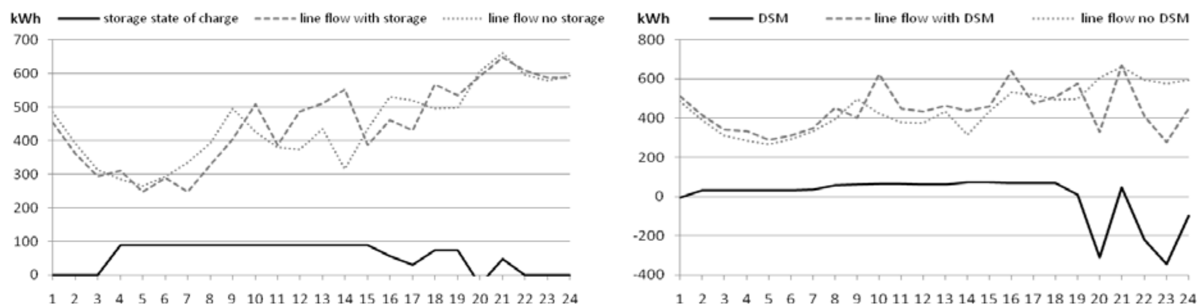

Figure 7: Storage operation, DSM operation and line flows in the course of a day in two scenarios. Summed over all nodes, there are 117 kWh storage capacity (left graph) and 1118 of the 1440 consumers have DSM appliances installed (right graph). (*Source: Own production*)

The grid capacity is sufficient for a securely functioning system in all scenarios. Even with high penetration of EV, grid capacity constitutes no severe shortage since line flows do not exceed 60% of thermal capacity limits at any time slice and any scenario, cf. Figure 7 (total limit 1850 kW). Moreover, alternative grid configurations such as a meshed grid would rather improve the situation. We conclude no grid reinforcements are required at 10 kV level. This does not mean grid extensions are not needed at 400 V low-voltage level. In order to undertake studies at 400 V level, an AC network model would be appropriate. Such model would incorporate reactive power and voltage drops which are of high relevance in low-voltage grids.

Figure 7 nicely illustrates how line flows narrowly coincide with storage use indicating that line flows are to a great extent driven by storage operations. We expected investment into storage and DSM to decrease the capacity utilization rate implying a drop in outage probabilities. While it is hard to assign a monetary value to drops in outage probabilities, it could then at least be stated that this percentage constitutes a further positive value of storage and DSM investments. Interestingly, though, we find that the introduction of storage devices could enhance line flows at certain moments, cf. Figure 7. This implies a stronger capacity use rate than in the absence of storage. Since storage devices are located at demand nodes, their demand for electricity sometimes passes from the grid supply point to the demand nodes and thereby increases grid capacity use. This happens notably in peak periods, i.e. midday. Accordingly, we conclude that storage devices can occasionally deteriorate and sometimes improve grid system reliability. All in all, no clear picture arises. The same holds true in the case of DSM operations. This result may have emerged because we include no penalty factor for the capacity use rate in the cost function.

A sensitivity study regarding the presence of EV in the year 2020 is illustrated in Figure 6. This is done to address the question of how EV modify the value of storage and load control. Obviously, a high number of vehicle charging augments demand and uncertainty and therefore strengthens the case for storage devices and DSM. If 10 % of the consumers own and drive EV, investment into DSM appliances is likely to rise by more than 50 % as compared to a world in absence of EV. All in all, results suggest that EV strongly induce investment into load control facilities. This result pretty much reflects the trivial fact that most EV are currently sold to home owners who also include smart metering systems. A potential alternative to smart EV home charging solutions could have been to install central storage devices and let EV owners charge whenever they like (so-called dumb charging). However, the value of storage increases only slightly in the EV scenario. This result indicates that installing DSM appliances for EV owners to allow for smart charging is a much better solution than installing central storage surrogates.

6. Discussion

What is the point of using a stochastic model? Results of the deterministic model indicate a tendency to under-investment as compared to the stochastic model's outcome. Figure 6 indicates that deterministic investment levels (dotted line) can be up to 50% lower than in the stochastic model (continuous lines) for storage. For both, storage and DSM, investment levels are consistently higher in the stochastic model. We estimate the value of the stochastic solution (VSS) to figure at around 0.5% to 5% of total system costs, indicating a gain in efficiency when using the stochastic model as opposed to the deterministic model. The VSS allows us to obtain the goodness of the expected solution value when the expected values are replaced by the random values for the input variables. We conclude that the cost of disregarding uncertainty lies at around 0.5% to 5% of total generation costs. On the other hand, the execution time of the stochastic model with a sample of 50 draws is roughly 15 times higher than the deterministic model. Computation times largely vary depending on the cost input data, though. All in all, we deem the stochastic model to be superior for it provides efficiency gains at reasonable additional CPU effort. The deterministic model appears to induce wrong long-term investment decisions.

The extensive form stochastic model solves in about the same time as the Benders decomposition model. If we were to extend the model so as to diminish stylization, we would expect the Benders model computation time to improve in comparison to the extensive form. Our conjecture is supported by studies such as Niknam et al. (2009). As a matter of fact, Benders decomposition is most suitable for outsized problems characterized by a capacious set of variables, nodes and parameters. In these conditions it may be valuable to isolate a group of decision variables and investigate the problem partially with Benders method. The decomposition model presented here shall constitute a basis for further models of larger size.

7. Conclusions

We have presented a DC load flow model applied to investment in storage and DSM facilities in a stylized medium-voltage grid. The model incorporates uncertainty in demand and wind output and uses Benders Decomposition to distinguish the investment choices from operative optimizations.

The model results indicate that grid reinforcements at 10 kV level are not necessary in any scenario. Capacity utilization rates do not hit the 60% bound which implies there is little harm to system stability.

Results suggest that storage devices are beneficial at capacity cost of up to 900 EUR/kWh in the stipulated conditions. This implies that relatively expensive storage technologies such as Nickel-Cadmium and Nickel-metal hydride storage should be profitable at current cost. Flywheels and large-scale capacitors are little competitive unless current cost is cut by factor four minimum.

DSM proves hardly beneficial in any scenario, especially not in the deterministic model. Investment is beneficial up to an all-inclusive cost of ca. 200 EUR per consumer. This break-even point (tolerance threshold) boosts when consumers own EV, implying that EV strongly encourage investment into load control systems. The finding reflects the actual fact that most EV are sold along with smart metering systems.

As a logical consequence, we identify that investment into storage is likely to crowd out investment into DSM appliances in our model setting. Since both options are direct alternatives for energy management, we predict 'smart meters' to be of little economic value to the system operator in the absence of EV. Unless governments strongly encourage DSM through obligations (beyond current obligations) and financial incentives or the promotion of EV, we believe that storage facilities are the better option for a vertically integrated distribution system operator facing the conditions of this model. We aimed at modeling conditions that would be representative for a section of a stylized distribution system in Germany.

It could be shown, that the stochastic model produces more efficient solutions compared to its deterministic counterpart. The cost of disregarding uncertainty lies at 0.5-5% of total generation cost. Our analysis demonstrates that a stochastic treatment of wind and demand patterns significantly augments the case for the use of storage. The break-even point for investment decisions into storage increases from 350 to 900 EUR/kWh when uncertainty of wind and demand are taken into account. Hence, the deterministic model leads to considerable under-investment into storage.

All in all, the results are highly sensitive to the assumed investment cost for storage and load management devices. EV are another cause for variations, yet, to a lesser extent.

There are a number of caveats to our analysis which constitute areas for improvement. Energy saving through demand response is entirely factored out. Our model may therefore underestimate the value of DSM to a minor extent. Furthermore, the investment cost for batteries is calculated on a diurnal basis with a fixed number of cycles per day. Fixing the cycles is a necessary step to obtain an exogenous cost figure but somewhat arguable since the cycles are endogenously determined in the model. Another drawback of our model is that some potential business cases of batteries and DSM are not included. Besides peak load reductions and network reinforcement deferral, Wade et al. (2010) point to other benefits of using storage devices. For instance, balancing markets as potential business field for batteries are not included in the present model. If balancing markets were to be considered, an hourly time resolution may not be optimal. Other shortcomings are the stylized grid configuration and the absence of ramping constraints for storage, which can be included in a further model of larger size.

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Appendix:

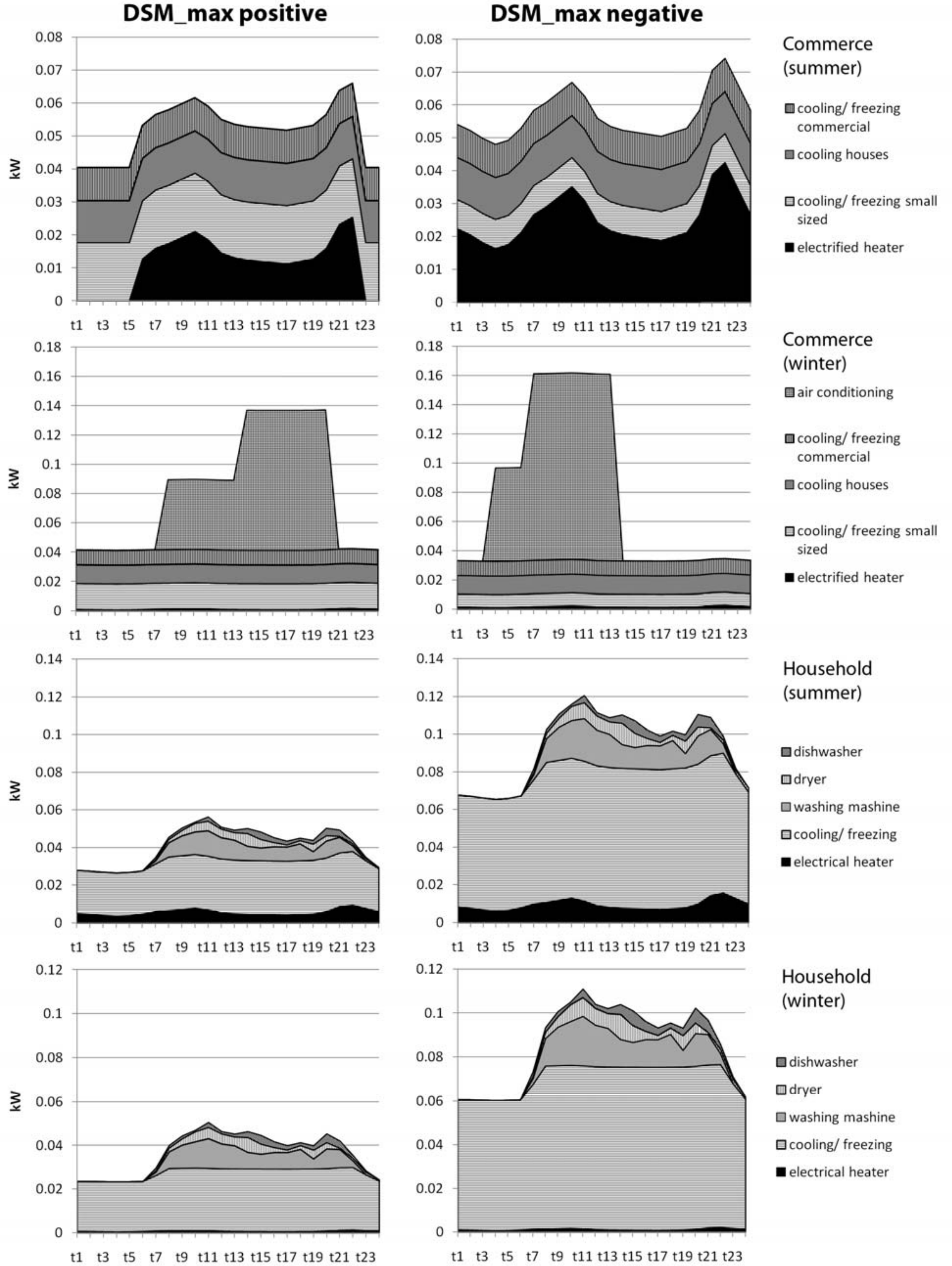

Figure 8: $DSM^{neg,max}$ and $DSM^{pos,max}$ for households and commercial units in kW during a day. EV profiles excluded. (*Source: Own production based on Stadler (2008), Grein et al. (2009)*)