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Modeling storage and demand management in power distribution grids

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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. This paper quantifies the related cost reductions in a simulation model of a simplified stylized medium-voltage grid (10 kV) under uncertain demand and wind output. Benders Decomposition Method is applied to create a two-stage stochastic optimization program. The model informs an optimal investment sizing decision as regards specific 'smart' 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 the 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.

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. 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. Recent legislation obliges German grid operators and utilities to install smart metering systems in new and refurbished dwellings. While legislative pressure spurs investment in smart metering, it may imply a negative effect on investment incentives in storage.

This paper scrutinizes load control and storage facilities as potential concurrent options targeting at electricity generation cost reductions and it quantifies possible substitution effects. Because of their common purpose, direct load control and centralised storage are two competing or possibly complementary solutions from the perspective of a vertically integrated power distribution system operator and utility. Moreover, it is tested whether storage and load control could alleviate the need for grid reinforcements by avoiding capacity shortages. The idea is that avoided shortage adds value to storage or DSM devices because of capacity upgrade deferral and added electricity sales [1]. Additionally to these issues, a methodological 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. The focus lies on short-term uncertainties and their impact on investment decisions.

There exists a broad range of literature dealing with storage sizing decisions. Refs. [2–6] perform numerical optimizations in a deterministic setting. Applications of stochastic patterns of generation and demand can be found in [7–10]. Tan et al. [10] 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. [11] apply stochastic wind generation patterns to a wind-battery system sizing model with deterministic demand. Ref. [12] do likewise with Plug-in Electric Vehicles (EV) as storage facilities.

The combination of intermittency of renewable resources and demand-side-management (DSM) is addressed in [13,14]. Concerning demand-side management (DSM), numerous research publications were found on investment decisions into DSM. Ki Lee et al. [15] assess investment into demand management systems for heating in a national case study for Korea. Paulus and Borggrefe [16] adopt a system-wide perspective of investment in DSM in a case study for Germany with focus on industrial consumers. Manfren et al. [17] deal with distributed generation planning, but avoid making any investment analysis. Neenan and Hemphill [18] investigate investment from a societal perspective while

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Nomenclature

Set

n	node with subset nn (1–5)
l	line (1–4)
t	hour (1–24)
s	technology (wind, solar, pv, chp, biomass, hydro, nuclear, hardcoal, lignite, gas)
sc	scenario (1–50)
$iter$	iteration (unlimited)

Variable

$D(n, t, sc)$	demand shifting (kW h)
$S_{in}(n, t, sc)$	storage inflow (kW h)
$S_{out}(n, t, sc)$	storage outflow (kW h)
$G(n, t, sc, s)$	generation (kW h)
$I_s(n)$	investment in storage (both kW and kW h)
$I_d(n)$	investment in a DSM system (absolute number)
$P(l, t, sc)$	phases angle difference (–)

Parameter

$q(n, t, sc)$	consumer demand (kW h)
$g_{max}(n, t, sc, s)$	maximum generation capacity (kW h)
$c_g(s)$	variable generation cost (EUR/kW h)
c_s	levelized investment cost for storage (EUR/kW h and EUR/kW)
c_d	levelized investment cost for DSM (EUR/kW h)
e	storage efficiency (%)
$d_{pos}(t,n)$	positive load shift capacity (kW)
$d_{neg}(t,n)$	negative load shift capacity (kW)
$lf(l,t,sc)$	electricity flow (kW)
$x(l)$	line reactance (Ohm)
$b(n,n)$	network susceptance matrix (–)
$h(l,n)$	weighted network matrix (–)
$lm(l,n)$	incidence matrix (–)
$lf_{max}(l)$	maximal capacity for line flow (kW)
$slack(n)$	slack variable (–)
$p(sc)$	probability (%)
λ_s	dual of fixing storage investment in subproblem (EUR/kW h and EUR/kW)
λ_d	dual of fixing DSM investment in subproblem (EUR per dwelling)
$\alpha(iter)$	sub-problem objective (EUR)
$I_{sMasterProblem}(n)$	investment in storage from master problem (both kW and kW h)
$I_{dMasterProblem}(n)$	investment in a DSM system from master problem (absolute number)
w	wind speed (meter/s)
k	Weibull scale parameter (–)
m	Weibull shape parameter (–)
r	random number with uniform distribution (0–1)

[19,20] find that investment into DSM appliances might not be all that profitable in general. It is intended to further investigate this claim in the present analysis.

This paper's contribution is unique in that no study explicitly compares the cost saving potential of storage and DSM in a comprehensive model including grid representation, endogenous investment and factors of uncertainty. Whilst an 11 kV distribution network representation in combination with a benefit analysis for storage and demand response measures can be found in [21], the present work complements their analysis by adding endogeneity to the investment into storage devices and DSM appliances as well as uncertainty of demand and wind generation. A further contribution consists in the application of Benders Decomposition Method to the stochastic program. Decomposition methods can be applied to numerous bi-level optimization problems in the energy sector, such as unit-commitment or capacity expansion. To the author's best knowledge, an application to evaluating storage and DSM infrastructure investment is unprecedented.

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

A basic direct current (DC) load flow model [22] is adapted to a situation with DSM and storage management. The model is designed as linear program under a cost minimization regime with hourly time resolution of two exemplary holidays (winter/summer). It is coded in General Algebraic Modeling System (GAMS) and can be solved with the solver CPLEX [23]. A vertically integrated system operator and utility 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. The agent can decide on whether to invest in storage and DSM technology as well as how to operate it. Still, the operator is able to shift the vertical demand curve left and rightwards through direct load control. The extensive-form cost-minimisation objective reads as follows:

$$\text{Objective(extensive form)} \quad \min_{\substack{I_d, I_s,\\ G, D,\\ S_{in}, S_{out}, P}} \sum^{SC} prob(SC) \cdot \sum^{N} \sum^{T} \left[\sum^{S} C_g(S) \cdot G(n,t,sc,s) + I_d(n) \cdot C_d + I_s(n) \cdot C_s \right] \tag{1}$$

The agent minimizes generation cost ($c_g \cdot G$) of each technology s as well as investment cost of DSM ($I_d \cdot c_d$) and storage ($I_s \cdot c_s$). Besides generation and investment, the agent can manipulate storage in – and outflow (S_{in} and S_{out}), shed or induce consumption (D) and transfer electricity from one node to another (P), subject to constraints detailed below. All variables are positive.

On the demand side, consumers are aggregated at each of the 10 kV/0.4 kV sub-station nodes n. Thus, a diurnal pattern of consumer demand (without DSM and storage), denoted by q, can be approximated using standard averaged load profiles weighted by the number of customers at the respective node. A perfectly inelastic, hence vertical demand function is assumed. This is a fundamentally different approach to demand response studies [24,25] and suitable here, since the focus lies on the producer side. There is no demand response. The consumer demand q is supplemented by contributions from DSM and charging of a battery. Note that demand is treated as stochastic parameter and it thus depends on the set sc.

Demand, supply and network flows constitute the energy balance constraint per node (2). It incorporates the simultaneity of generation and consumption as well as the first Kirchhoff rule

$$\text{Energy balance} \sum^{S} G(n,t,sc,s) + S_{out}(n,t,sc) - q(n,t,sc) - D(n,t,sc) - S_{in}(n,t,sc) - \sum^{nn} b(nn,n) \cdot p(nn,t,sc) = 0 \quad (2)$$

On the supply side, a setup is considered where each generation technology $s \in S$ at time $t \in T$ and node $n \in N$ contributes an amount G to total electricity generation at marginal unit cost c_g, up to its capacity limit g_{max}, which is exogenous, time-dependent and treated as stochastic parameter

$$\text{Generation limit} \quad g_{max}(t,n,sc,s) - G(t,n,sc,s) \geqslant 0 \quad (3)$$

Ideally, investment decisions relating to DSM and storage should consider grid infrastructure constraints because load shifting may serve as a mean to avoid capacity shortage and system outage probability. [1] explicitly take into account this "delaying capacity replacement" value of DSM devices when appraising the worthiness of DSM. In the model presented here, a number of grid-related constraints are included in order 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 lm, where $lm = 1$ means that line $l \in L$ starts at node n, while $lm_{l,nn} = -1$ means that it ends at node nn. Weighting each line with the inverse of its reactance x, the matrix h (4) can be obtained and thus the network susceptance matrix b (5). If the phase angle of node n at time t is denoted by P, the flow along line l at time t is given by Eq. (6), where the sign of lf depends on the direction of the flow. Since P is defined relative to a reference bus, slackness conditions $slack \cdot P = 0$ hold, and a $slack(1) = 1$ is chosen (that is, $P = 0$) to set node 1 as the reference node (8). Physical line capacity constraints are included (7). In a DC network, only the thermal limit is relevant. If the grid capacity constraint was violated – which turns out not to be the case in this specific application – the operator would incur losses through foregone sales of electricity. Additionally, the capacity shortage is fixed manually ex-post, a penalty cost is applied and the model is re-run with new capacity figures

$$\text{Weighted Network Matrix} \quad h(l,n) = \frac{1}{x(l)} lm(l,n) \quad (4)$$

$$\text{Network susceptance} \quad b(n,nn) = \sum^{L} h(l,n) \cdot lm(l,nn) \quad (5)$$

$$\text{Line flow} \quad lf(l,t,sc) = \sum^{N} h(l,n,sc) \cdot p(l,n,sc) \quad (6)$$

$$\text{Line flow limits} \quad -lf_{max}(l) \leqslant lf(l,t,sc) \leqslant lf_{max}(l) \quad (7)$$

$$\text{Flow convention} \quad slack(n) \cdot p(n,t,sc) = 0; \quad slack(1) = 1 \quad (8)$$

The second set of constraints relates to DSM. Investments in load control infrastructure for DSM have the benefit of allowing intertemporal shifts of electricity demand. When direct load control is made possible, parts of electricity consumption may be shifted to earlier or later stages up to power limits d_{neg} and d_{pos}, respectively (9). The system operator does this with the aim of saving cost. d_{neg} represents the power limit of energy that can be saved at each time by shifting load away to another period of the day. Accordingly, d_{pos} is the potential that can be added at each time. Note that both parameters are defined as positive numbers while contributions must balance to zero over time (10). The option for DSM is reflected in an additional contribution to total demand, D.

DSM appliances may yield peak load reductions and thereby justify infrastructure reinforcement deferral. However, it is disregarded that the installation of DSM appliances could yield overall demand reductions. This is done not only because projections of demand reduction through DSM devices appear to be fairly uncertain and consumer-specific, ranging between zero and 20% [13,26,27]. The focus is on direct load control exerted by the system operator. Demand response measures and related consumption savings driven by consumer behavior are beyond the scope of this operatorś cost-minimization model.

Storage facilities in the distribution network can take up a positive charge S_{in} at time t, convert it (with some loss e) and subsequently provide positive amounts S_{out}, where the overall balance is governed by capacity constraints (12) as well as input and output kW power constraints, which are set equal to kW h capacity constraints for reasons of simplicity (13). Note that energy capacity is set 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 (11)

$$\text{DSM Limits} \quad d_{neg}(n,t) \cdot I_d(n) \leqslant D(n,t,sc); \quad D(n,t,sc) \leqslant I_d(n) \cdot d_{pos}(n,t) \quad (9)$$

$$\text{Constant total demand} \quad \sum^{SC} \sum^{T} D(n,l,sc) = 0 \quad (10)$$

$$\text{Storage balance} \quad \sum^{T} [S_{in}(n,t,sc) \cdot e - S_{out}(n,t,sc)] = 0 \quad (11)$$

$$\text{Storage capacity limits} \quad \sum^{T} S_{out}(n,t,sc) - \sum^{T-1} S_{in}(n,t,sc) \cdot e \leqslant 0; \quad \sum^{T} S_{in}(n,t,sc) \cdot e - \sum^{T-1} S_{out}(n,t,sc) - I_s(n) \leqslant 0 \quad (12)$$

$$\text{Storage power limits} \quad I_s(n) - S_{out}(n,t,sc) \geqslant 0; \quad I_s(n) - S_{in}(n,t,sc) \quad (13)$$

$$\text{Non-negativity} \quad G(n,t,sc) \geqslant 0; \quad S_{out}(n,t,sc) \geqslant 0; \quad S_{in}(n,t,sc) \geqslant 0 \quad (14)$$

The problem is formulated as two-stage stochastic optimization program, with initial investment at the first stage and operative optimizations at the second stage, see Fig. 1. Benders Decomposition Method is applied with conflicting variables being initial investment levels into storage and DSM [28]. 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 this 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 than 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, see Fig. 1. The Benders approach reduces computation effort as compared to solving the extensive form expected-value-problem

$$\text{Master Objective} \quad \min_{I_s, I_d} \alpha + \sum^{N} I_d(n) \cdot C_d + I_s(n) \cdot C_s \quad (15)$$

$$\text{Benders cut} \quad \alpha(iter-1) + \sum^{N} [\lambda_d(n) \cdot (I_d(n,iter) - I_d(n,iter-1)) + \lambda_s(n) \cdot (I_s(n,iter) - I_s(n,iter-1))] \leqslant \alpha(iter) \quad (16)$$

$$\text{Sub objective} \quad \min_{\substack{G,D,\\ S_{in},S_{out},p}} \sum^{SC} prob(SC) \cdot \sum^{N} \sum^{T} \left[\sum^{S} c_g(s) \cdot G(n,t,sc,s) \right] \quad (17)$$

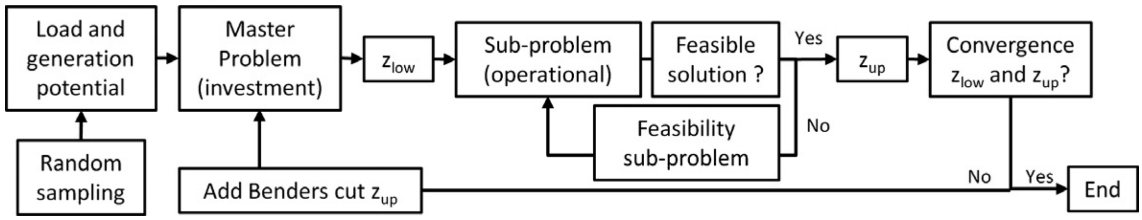

Fig. 1. Algorithm used for solving the two-stage problem. *Source*: Own illustration.

Fixing variables to results of Master Problem

$$I_s = I_{s,Masterproblem}; \quad I_d = I_{d,Masterproblem}; \quad duals \lambda_d(n) and\ \lambda_s(n) \tag{18}$$

The relaxed master problem objective (15) includes α, the objective value of the sub-problem and is restricted by the Benders cut (16). The recursive sub-problem objective function is Eq. (17). Concerning the Benders cut, λ_d and λ_s correspond to the duals of the constraints (18) which fix the variables I_d and I_s to their values resulting from the corresponding master problem. α_{iter} is a decision variable setting the lower bound to the recourse problem after each iteration *iter*. Note that the iteration counter is added in the variable sets in Eq. (16) unlike all previous equations.

3. Application to a simple distribution system

This section describes the application of the presented model to a simple five-node 10 kV medium-voltage-grid with characteristics representative for a typical distribution system structure in sub-urban Germany. Assumptions regarding the application are detailed hereafter.

3.1. Generation

Nine technologies are part of the generation mix in this application: Six technologies – hydro, nuclear, lignite, hard coal, gas and biomass – have generation capacities with full availability at any time (up to a technical factor, e.g. due to maintenance requirements, taken from [29]). Three technologies have varying availability, with wind output being treated as stochastic parameter. Small-scale heat-controlled CHP diurnal patterns follow an approximation in [1] for both winter and summer and they are weighted by a seasonal factor 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 central German location [30] (see Fig. 2).

It is assumed that generation capacities are distributed differently between the nodes of the 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}, specifying the maximum available power from each generation technology per time slot and per node. Incremental generation cost is illustrated in Table 1. The figures are independent from the utilization rate of a generation technology.

Special attention is given to generation data of wind power which is treated as stochastic parameter. A Weibull probability distribution is used to create random samples of wind speeds just as in [11]. Eq. (19) includes *w*, the wind speed, *r*, a random number uniformly distributed between 0 and 1, a scale and a shape parameter *k* and *m*. The shape parameter equals 2 (typical for Central Europe) and the scale parameter varies by time-of-day [7,11,14] and it is calibrated to match a typical on-shore location in the center of Germany

Inverse of the Weibull cumulative distribution function

$$w = -k \cdot [\ln(1 - r)]^{\frac{1}{m}} \tag{19}$$

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 kW h. The number of wind rotors and their conversion efficiency are calibrated so as to match a share of wind energy in total production conform to projections in [29]. Cut-in, rated and cut-out wind speeds are indicated in [11]. The maximum of wind output is scaled to 537.44 kW with 800 m^2 of rotor surface installed. The simulated random diurnal profiles (Fig. 3) of wind output are validated against observed data in [14,31] (Fig. 4) and simulations in [11].

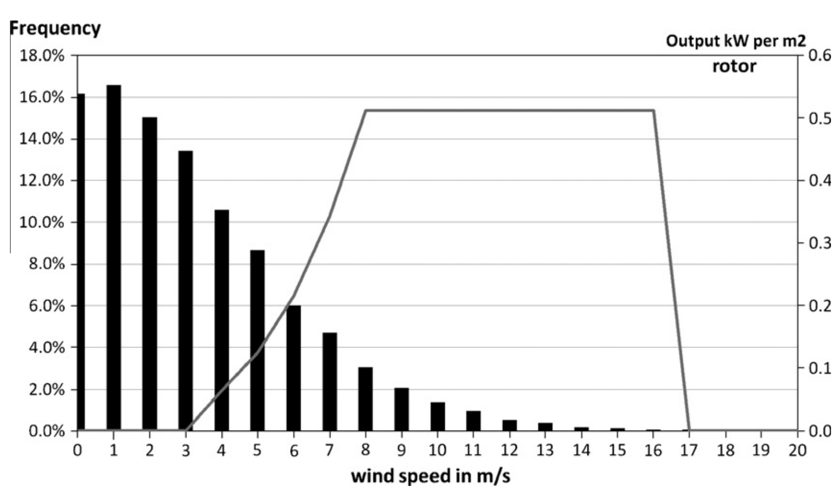

Fig. 2. Frequency and power output under wind speeds with average wind speed 5.22 m/s at specified cut-in and cut-out rates. *Source*: Own production based on [11].

Table 1
Available capacity and projections of marginal generation cost incl. carbon cost in 2020. *Sources*: Based on [29].

Available energy (per day, aggregated over all nodes)											
Demand peak [kW]		1100									
Technology type	Source	Wind time-dependent	PV time-dependent	CHP time-dependent	Biomass flexible	Hydro flexible	Nuclear flexible	Lignite flexible	Coal flexible	Gas flexible	Total
Installed capacity (Germany 2020) [GW]	Prognos et al. (2010)	40.9	33.3	4	7.85	7.7	6.7	22.4	28.5	24.4	175.75
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		10.6%	57.1%							
Technical availability (where relevant)	Prognos et al. (2010)				88%	90%	93%	86%	84%	84%	
Installed capacity [kW] (in model)	Calculation	537.44	437.57	52.56	103.15	101.18	88.04	294.34	374.50	320.63	2309.42
Available energy, per day [kW h] (in model)	Calculation	Varying	Varying	Varying	2178.57	2185.51	1965.07	6075.27	7549.94	6463.81	31638.31
Technology	Wind	PV	CHP	Hydro	Biomass	Nuclear	Lignite	Coal	Gas		
Marginal cost [EUR/kW h]	0.0001	0.0002	0.0003	0.0004	0.0005	0.010	0.04	0.038	0.07		

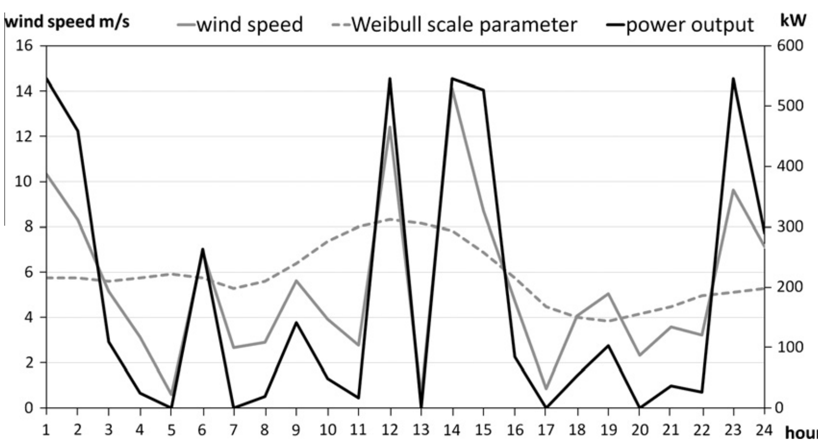

Fig. 3. Simulated diurnal profiles of mean wind speed and output in winter (right). *Source*: Own production.

The fact that wind speed is simulated as a Markov, non path-dependent, process may imply a slight over-valuation of investment into flexible storage and DSM.

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. From the perspective of 2011, the year 2020 is a reasonable representative 'average' year regarding the penetration of renewable energy resources over the life-time of a storage or DSM investment. Therefore, a hypothetical generation limit of each generation technology is derived from a forecast for the year 2020 given in [29]. The available installed capacity in Germany is scaled down. The share of installed capacity versus yearly peak demand in the model network corresponds to that of the national grid [29]. Optimized generation profiles are outlined in the results section.

3.2. Demand

360 dwellings are assumed to be connected per 10–0.4 kV transformer. Each consumer unit is equivalent to a 1.99-person household, a representative mix for Germany [29]. The share of commerce and households is 21% and 79% in the model. The industrial sector is left out in the model because – by law – industrial consumers are already equipped with appliances for DSM when yearly consumption exceeds 100,000 kW h.

A random sampling method is utilized for the simulation of demand realizations. Random sampling techniques are popular in risk analysis and used in research on electricity topics [10,11]. Simulated stochastic demand values (Figs. 5 and 6) are drawn from a normal probability distribution with time-varying mean and standard deviation under the assumption of independence between wind power output and demand. The simulation creates 50 profiles which include the possibility of very extreme events. The mean values of demand realizations are taken from [32] and averaged over months and types of day so as to create two single daily mean profiles per year with 24 h each (summer/winter) as indicated in Fig. 7. Standard deviations of demand variability are known to the optimizing agent based on empirical demand realizations at the EEX wholesale intraday market [33]. Deriving medium-voltage demand variability from wholesale market demand fluctuations is reasonable for model systems with aggregation of a high number of consumers. The more consumers are aggregated, the less volatile is energy consumption [34]. Fluctuating demand profiles outlined in [14,35], projected profiles for 2020 in [13] and empirical data in [36,31] were consulted for validation of the sampled demand profiles here. Maximum and minimum sampled demand in the modeled system figure at 1100 kW and 240 kW, excluding EV. This is a spread of factor five and a deviation of 60–90% around the

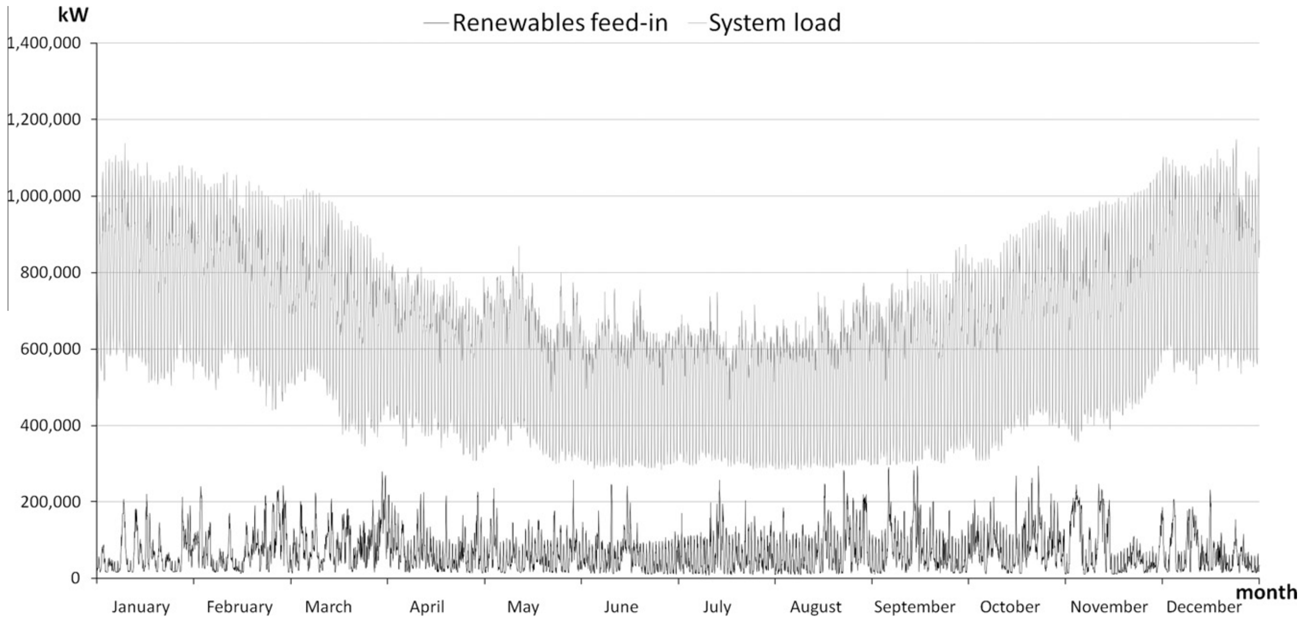

Fig. 4. Feed-in and load of non-power-metered consumers in 2010 in a Western German distribution grid. Source: [37].

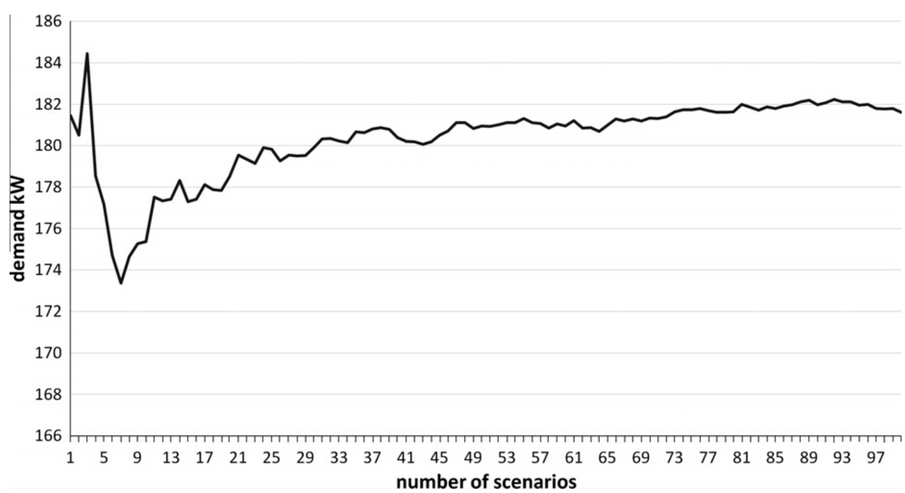

Fig. 5. Sampled demand profiles in winter and summer. Source: Own production based on [32].

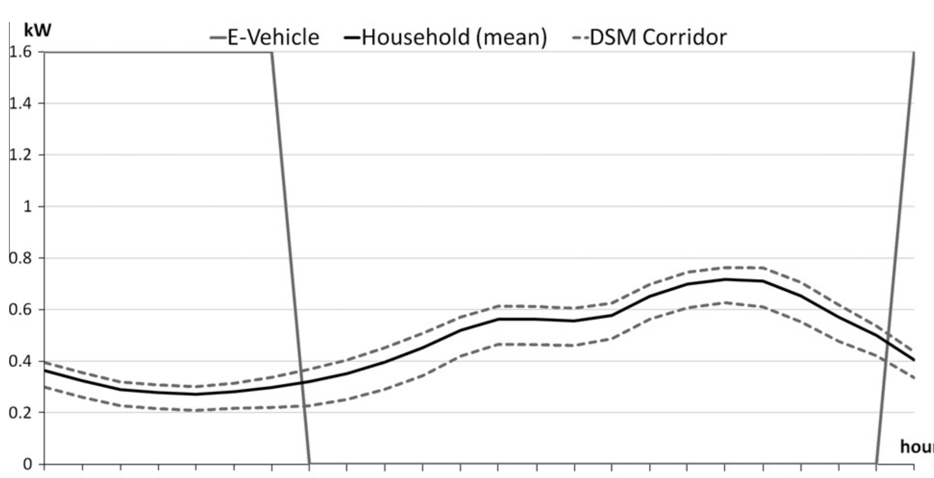

Fig. 6. Convergence of sample demand mean with an increasing amount of scenarios. *Source*: Own production.

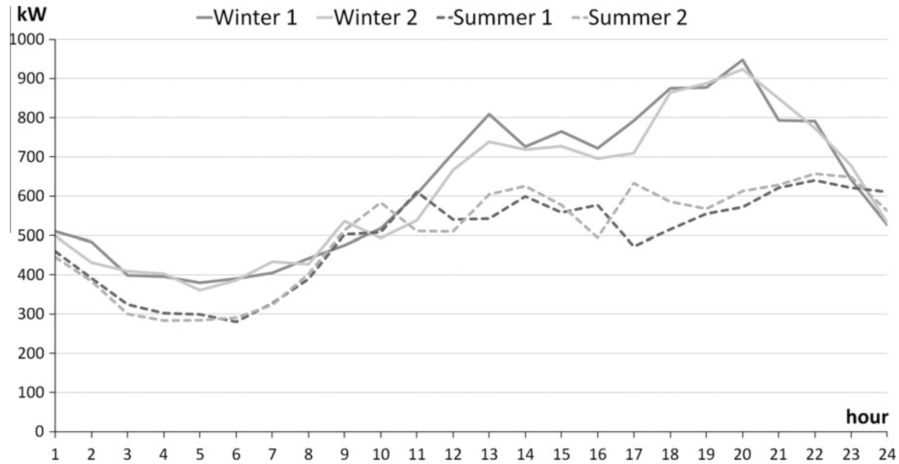

Fig. 7. Deterministic mean standard load profile with corridor for upper and lower bounds of the DSM potential on a winter holiday. Additionally, the graph plots one EV charging profile. *Sources*: Own production based on [32,35,37].

Table 2
Storage investment cost data compiled from various sources. Mechanical bulk storage included for reference but not considered in the calculations. *Sources*: [27,39–41]

Conversion	Storage type	EUR (kW h)	EUR (kW)	Cycles (100%)	Efficiency (%)
Mechanical	Supercapacitor	3800–4000	100–400	10,000–100,000	95–100
	Flywheels	1000–3000	300	20,000–60,000	90–95
	Pumped hydro	60–150	500	20,000–50,000	70–85
	Compressed air	30–120	550	9000–20,000	70–80
Electro-chemical	Nickel–metal hydride	700–800	-	500–3000	65
	Nickel–Cadmium	350–800	175	1000–3000	60–70
	Sodium–sulfur	200–900	150	2000–3000	85–90
	Lithium–ion	200–500	175	3000–6000	95–100
	Vanadium redox-flow	100–1000	175	2000–3000	75–85
	Zinc–bromine	50–400	175	>2000	70
	Lead acid	50–300	175	200–1100	75

average system demand (561 kW). Empirical data from 2010 in [37] exposes a spread of factor 4 between peak and lowest demand. For an isolated island with 90,000 inhabitants, Ref. [14] show that the spectrum of demand values ranges 75–100% of the mean value either way while maximum and minimum yearly demand differ by factor eight. The spread of demand simulations in the model system here is thus comparable with empirical profiles at other distribution systems.

In this application electricity consumption of EV is incorporated into the stochastic reference demand q. A load pattern is assumed with 8 h domestic charging time at a rate of 1.6 kW, referred to as Level 1 charging speed, see Fig. 7. A full charge per night (12.8 kW h) would correspond to a 100 km range. Note that EV are not equivalent to storage facilities in the model. This implies no vehicle-to-grid technology is considered here. Uncontrolled EV solely behave as additional consumers whose load can be curtailed and shifted if DSM appliances are installed. Charging behavior 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.

3.3. Load control

The DSM potential for average households and commerce is derived from a study report for the City of Mannheim, Germany [35] and triangulated with [38]. EV availability is added to the DSM potential. The resulting potential can be observed for each time slice in Figs. 7 and 13. Fig. 7 plots an average load profile for a household with the corridor of maximum and minimum load when DSM appliances are installed. Positive and negative shifts are possible and their potential is asymmetric. The potential to increase energy load at each time, d_{pos}, is generally larger than d_{neg}.

The total cost of equipment for DSM figures in between 160 and 350 EUR per installed system [27]. The application here refers to the so-called Advanced Metering System (AMM), which includes two-way communication via an integrated router gateway in each dwelling. This system enables time-of-use pricing and direct load control up to the capacities detailed in Fig. 13. The cost figure includes investment into hardware such as meter, gateway, router and its initial installation. In order to calculate lifetime cost, a 6.5% annual discount rate is applied with a lifetime of 16 years [27].

3.4. Storage

The model considers investment into a central large-scale stationary battery with endogenous capacity and conversion efficiency factor of 75%. The focus is 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, the cost input data is varied. Approximated cost data of equipment and installation is compiled in Table 2 for reference [39,41]. In the cost considerations, a life-time of 3000 cycles is assumed at 80% depth of discharge with one cycle being completed every three days, hence a life-time of 12 years. To facilitate tractability and increase computation speed, the three dimensioning vectors of a storage unit –

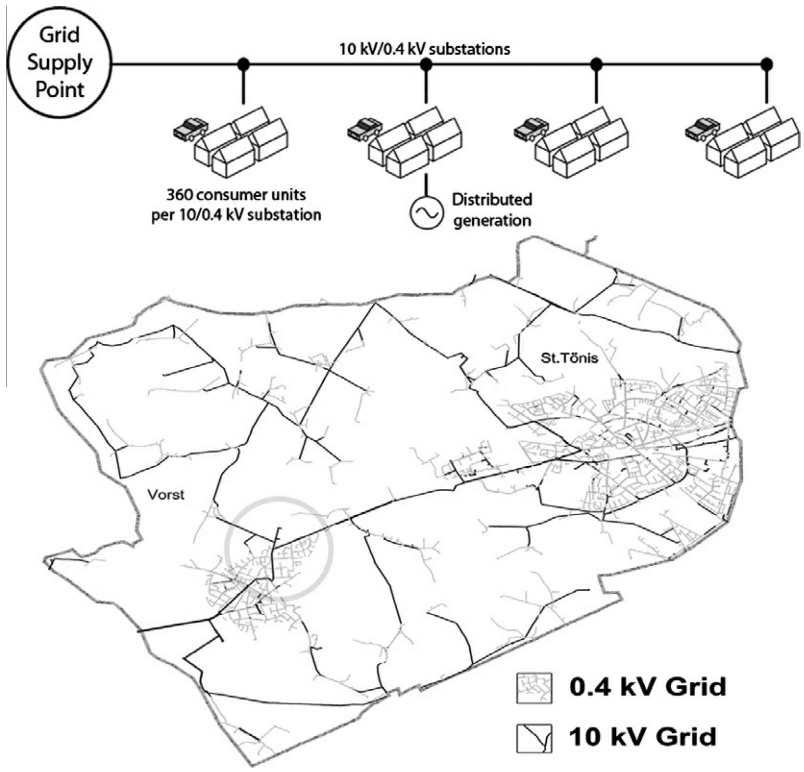

Fig. 8. Stylized 5-node distribution grid configuration in series connection and encircled location inside a reference distribution grid in Western Germany. Source: Own illustration and based on [31].

capacity in kW h, charge rate and discharge rate in kW – are all set equal in this analysis. Such assumption is 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.

3.5. Grid

A stylized configuration is simulated with characteristics that approximate realistic grids, as illustrated in Fig. 8 [42,31]. The grid representation used in the case study here consists of five nodes, one of them the grid supply point (GSP) and additionally demand nodes with 10 kV/400 V transformers. The nodes are connected in line so as to simulate a 'worst-case' topology. The analysis restrains to the 10 kV-level of a stylized distribution network. An application of the presented DC flow model to a 400 V level is delicate for the DC load model does not include reactive power. At 400 V level, voltage drop limits and reactive power are of high relevance. Large-scale generation, including wind turbines and pump storage, is assumed to be connected at the 10 kV level, whilst DG and EV are part of the underlying 400 V grid. 10 kV overhead lines have a lateral surface of 70 mm^2 with associated capacity of 185 Ampere. In a 10 kV DC setting this results in a maximum capacity limit of 1850 kW. A typical reactance of the 10 kV network is around 0.4 Ohm/km [1,42]. Upgrade costs of overhead circuits in a comparable 11 kV grid lie at 3102 €/MW/km [1]. It is assumed all lines are 2 km long and line flows do not incur transmission losses. Grid reinforcements are not included as variable in the model equations delineated above but calculated ex-post in case grid capacity represents a shortage.

4. Results

The linear problem is implemented in GAMS, using the solver CPLEX 9.0 [23] with standard options. A 1.3 GHz CPU machine executes the stochastic linear program for one exemplary day in between 2 and 8 min 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 Fig. 9, storage devices are found to pay off at investment cost below 850 EUR/kW h of capacity. For instance, if costs amount to 300 EUR/kW h, storage devices are profitable up to a size of roughly 0.5 MWh capacity (and MW power limit) in the framework of the model, depending on the degree of EV penetration. That corresponds to about one fifth of installed generation capacity (2309 kW) and one half of peak demand (1100 MW) in the system. In total, it is found that less than 1% of aggregated electricity consumption is stored in most scenarios (Fig. 10). 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 contrast, super-capacitors and flywheels need to severely cut their cost in order to become competitive. 2011 investment cost lies between 2000 and 4000 EUR/kW h.

Appliances for DSM prove hardly profitable in the deterministic model setting, which echoes a finding of [19,20]. 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 2009 cost for AMM systems lies 260 EUR and projections for 2020 figure at a minimum of 160 EUR (EcoFys, 2009). The break-even point (tolerance threshold) for investment into DSM increases up to 700 EUR when 10% of consumers own

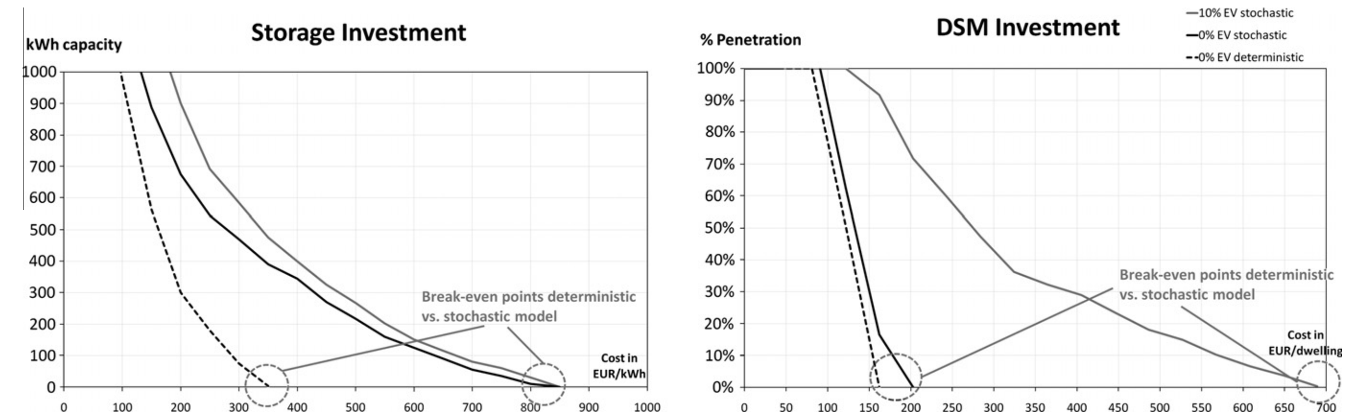

Fig. 9. Investment into storage and DSM under varying investment cost and penetration degree of electric vehicles. The dotted line corresponds to results of the deterministic model. Curves are interpolated from several mode runs. *Source*: Own production.

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 management than does DSM.

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, as shown in Fig. 10 (total limit 1850 kW). Moreover, alternative grid configurations such as a meshed grid would rather improve the situation. It can be concluded that no grid reinforcements are required at 10 kV level in the model setting. The grid representation constitutes a stylized grid with realistic characteristics so as to be able to generalize conclusions to a certain extent. While the stylized grid seems to be well equipped for additional future loads, 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.

At specific hours in summer, the system exposes an over-supply of renewable feed-in. In these moments, DSM and storage operations are crucial. Figs. 10–12 illustrate how load profiles are adapted to better align with renewable feed-in. Overall, the system predicts between 50% and 60% of demand to be covered by renewable energy generation in the absence of storage and DSM, which is more optimistic than future projections for Germany in [29] (34% renewable generation by 2020). The use of storage and DSM slightly improves the coverage through renewable resources. Fig. 10 illustrates how line flows narrowly coincide with storage use indicating that line flows are to a great extent driven by storage operations. It is found that the introduction of storage devices enhances line flows at certain moments, see Fig. 10. This implies a stronger capacity use rate than in the absence of storage, notably in peak periods, i.e. midday. All in all, grid system reliability is not affected by storage and DSM operation since line flows do not exceed a critical bound at any moment, neither with nor without storage and DSM.

A sensitivity study regarding the presence of EV in the year 2020 is illustrated in Fig. 9. 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 sold to home owners along with 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.

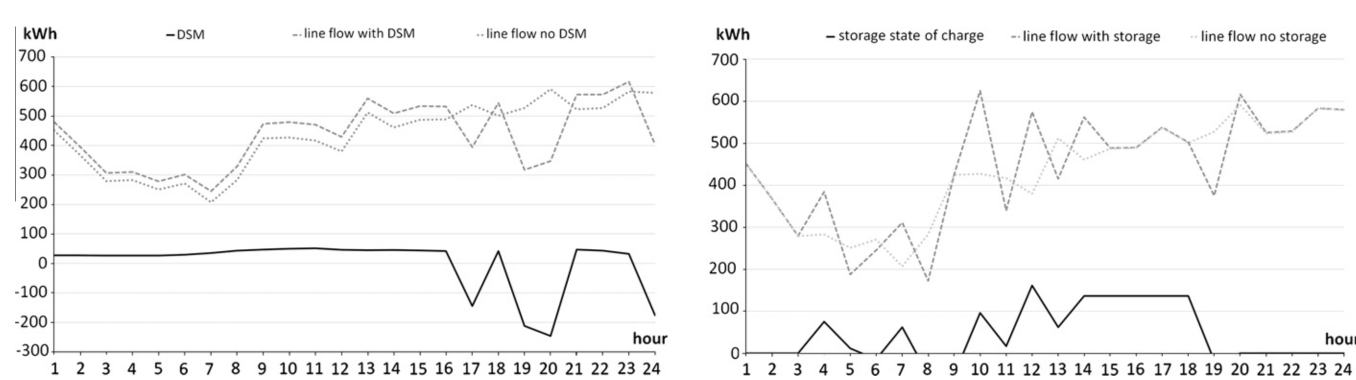

Fig. 10. Storage operation, DSM operation and line flows in the course of a day in two scenarios. Summed over all nodes, there are 309 kW h storage capacity (left graph) and 807 of the 1440 consumers have DSM appliances installed (right graph). *Source*: Own production.

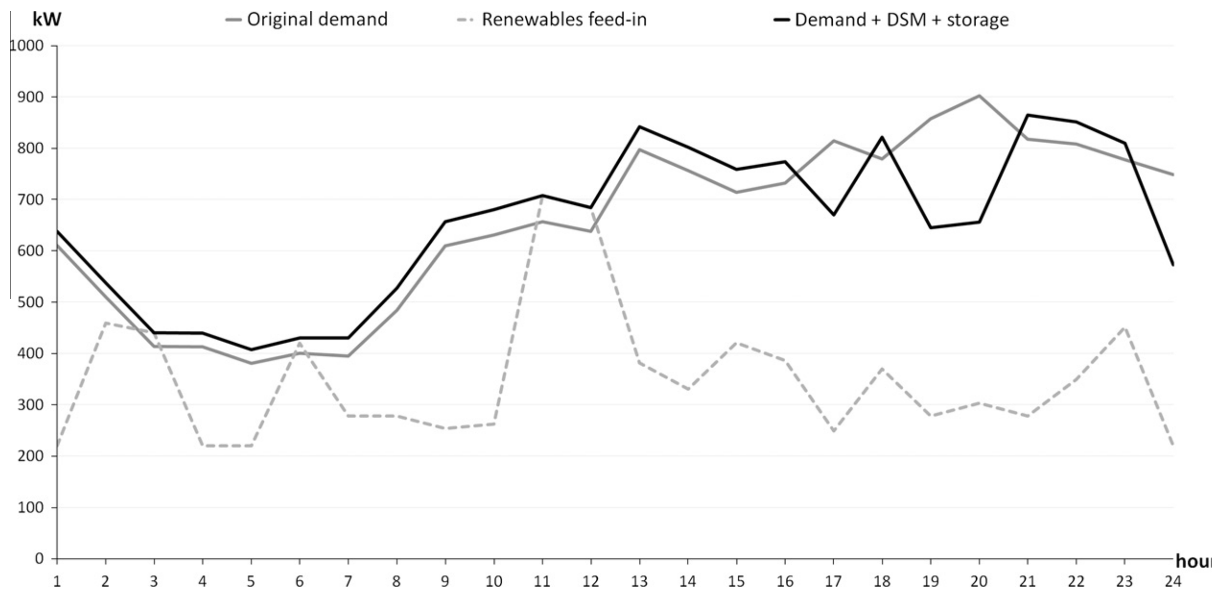

Fig. 11. Renewables feed-in, original demand and load after storage and DSM shifts. *Source*: Own production.

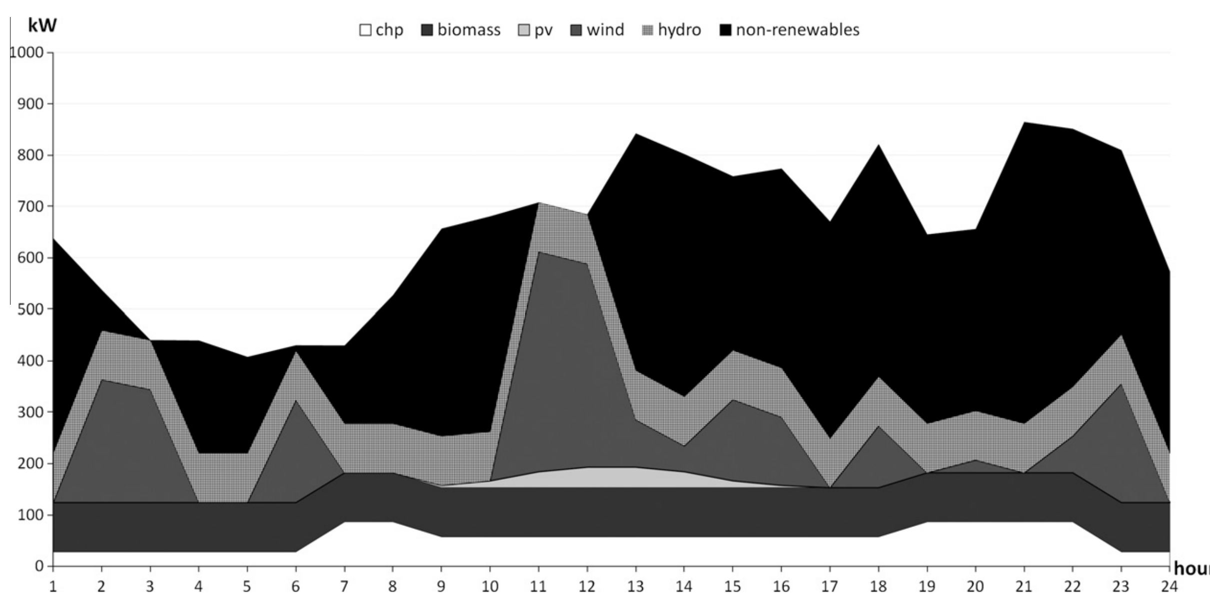

Fig. 12. Generation profile in a specific scenario on a winter day. *Source*: Own production.

5. Discussion

It was found out that investment into storage is in general relatively more profitable than DSM systems from an operator's point of view. Practical and management aspects strengthen the position of central stationary batteries for storage versus DSM systems. Central storage devices are much easier to handle than a high number of dispersed DSM systems. The latter also require decent communication systems for interaction between consumers and supply in order to be fully effective [43]. Furthermore, Storage offers a constant load potential at any time. When installing DSM systems, the availability of DSM potential is dependent on the consumer and it may be temporarily very low. Thus, storage devices offer more flexibility as compared to DSM systems. A drawback of storage is that it requires higher upfront investment cost and it may not go with consumption reductions in general. Consumption reductions can be reached through demand response programmes and the offering of variable tariffs with the help of DSM systems. This latter effect (demand response) is left out in this paper's analysis.

What is the point of using a stochastic model? Results of the deterministic model indicate a tendency to under-invest as compared to the stochastic model's outcome. Fig. 9 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. The value of the stochastic solution (VSS) is estimated to figure at around 0.5–5% 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. It can be concluded that the cost of disregarding uncertainty lies at around 0.5–5% of total generation costs. On the other hand,

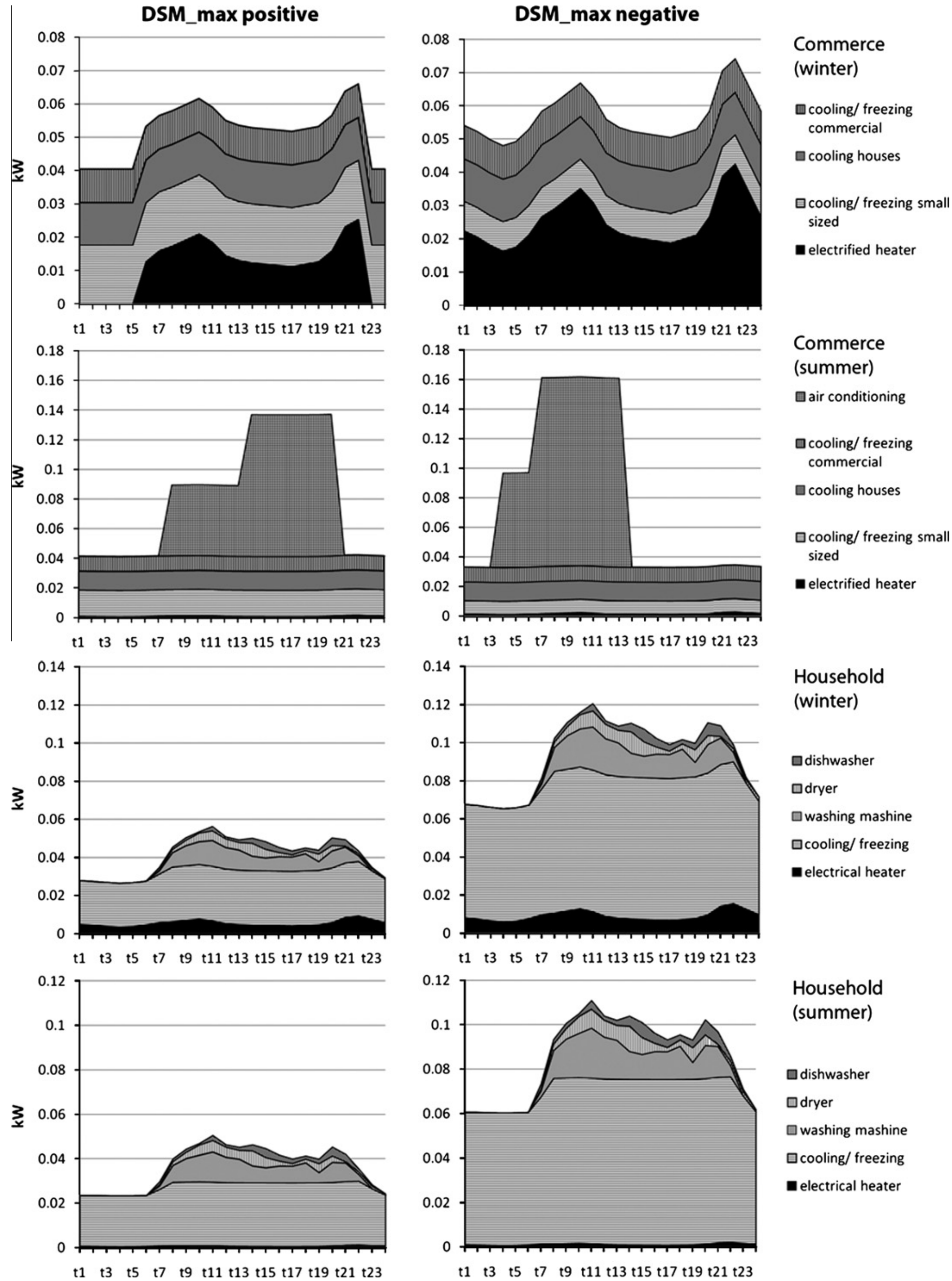

Fig. 13. d_{neg} and d_{pos} for households and commercial units in kW during a day. EV profiles excluded. *Source*: Own production based on [37,35].

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, the stochastic model is superior for it provides efficiency gains at reasonable additional CPU effort. The deterministic model appears to induce wrong long-term investment decisions and under-values the flexibility provided by storage and DSM.

The extensive form stochastic model solves in about the same time as the Benders Decomposition Model. If the model was extended so as to diminish stylization, the Benders model computation time should improve in comparison to the extensive form. This conjecture is supported by the fact that 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.

6. Conclusions

This paper presents 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. It is shown how Benders Decomposition Method can be meaningfully applied to a small-scale investment problem in a network-constrained industry. The model is capable of reflecting multiple formats of short-term uncertainties in system constraints at the operational dispatch stage.

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 850 EUR/kW h under the stipulated conditions. This implies that relatively expensive storage technologies such as Nickel–Cadmium and Nickel-metal hydride storage are profitable at current cost. Flywheels and large-scale capacitors are not competitive unless cost is reduced to 25% of 2011 cost.

DSM is not beneficial in any scenario, particularly in the deterministic model. Investment is beneficial up to an all-inclusive cost of roughly 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 advanced ('smart') metering systems.

As a logical consequence, it is found that investment into storage is likely to crowd out investment into DSM appliances in the model setting. Since both options are direct alternatives for energy management, 'smart meters' seem 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, storage facilities are the better option for a vertically integrated distribution system operator facing the conditions of this model. The present paper 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 than its deterministic counterpart. The cost of disregarding uncertainty lies at 0.5–5% of total generation cost. The 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 850 EUR/kW h 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. The calculations indicate that the value of storage strongly varies with the intermittency of wind output. The value of DSM is less sensitive to wind but more sensitive to EV penetration.

There are a number of conceptual caveats to the analysis which constitute areas for improvement. Energy saving through demand response is entirely factored out. The 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 this model is that some potential business cases of batteries and DSM are not included. Besides peak load reductions and network reinforcement deferral, [21] 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. 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. An application to a grid of larger size is planned for a subsequent paper.

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Appendix A

Fig. 13

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