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Long-term projections of the hourly electricity consumption in Danish municipalities

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ABSTRACT

To assess future challenges for the energy system, the transmission - and distribution grids, long-term projections of the spatial distribution of electricity consumption with an hourly resolution is important. Based on 2015 data from hourly meters in Denmark, we develop a model that converts national projections of the annual electricity consumption to projections of the hourly consumption in Danish municipalities. Due to different weights and consumption profiles for categories of customers, both the level and the hourly consumption profile differ between municipalities; also future changes will differ.

To illustrate future changes, the latest official projection by the Danish Transmission System Operator is used, showing a moderate increase in classic consumption and a considerable increase in total consumption due to electrification of the heating and transport sectors. In addition, the projection includes a number of large datacentres. Electric vehicles and individual heat pumps will determine the future consumption profile in municipalities, while large datacentres mainly determine the level of consumption at specific nodes in the grid. That is, electric vehicles and heat pumps challenge both the energy system, the transmission and the local distribution grids, while large datacentres mainly challenge the energy system and specific nodes in the overall transmission grid.

1. Introduction

To assess future challenges for the energy system, the transmission - and distribution grids, long-term projections of the spatial distribution of electricity consumption with an hourly time-resolution is important. In energy system models like EnergyPlan, Balmorel and Markal/Times and in models used for grid planning often the future hourly consumption profile is assumed equal to the base-year profile.[1] However, as shown in this paper due to structural changes and new categories of consumption both the level and the hourly profile of demand may change considerably. Based on hourly metering of the electricity consumption by individual customers, aggregated into categories of customers and municipalities, we develop a model that converts a national projection of the aggregate annual consumption to a projection of the hourly electricity consumption at the municipality level. In an earlier paper (Andersen et al. [5]), a model projecting the hourly consumption profile in different local areas in Denmark West was developed. The basis for that model was hourly metering at transformer stations and statistics for the hourly electricity consumption by categories of customers at the national level. Assuming that 1) “for each category of customers, the consumption profile is identical for all local areas”, and 2) that “one and only one transformer station delivers to a specific local area”, the weight of categories in each local area was estimated. Relaxing these assumptions, this paper presents a new model based on data from hourly metering of individual customers aggregated into categories and municipalities in Denmark. That is, this paper contributes with a new model covering all municipalities in Denmark, and methodologically the novelty is that the weight and hourly consumption profile of each customer category is calculated from meter data, and therefore that both the weights and customer profiles differ between municipalities.

Finally, using the model applying the latest projections of the annual electricity consumption used in the planning by the Danish Transmission System Operator (TSO) “Energinet.dk”, future changes in the level, the hourly profile and the spatial distribution

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[1] The EnergyPlan model is described in Lund H. [1], an application of Balmorel is given in Wiese el al. [2], the Markal/Times model is described in IEA-ETSAP TIMES [3] from where the model may be downloaded. Finally Connolly et al. [4] reviews a long list of energy system models used for analysis of the integration of renewable technologies.

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of the aggregated electricity consumption is evaluated. A main conclusion from the projection of the hourly electricity consumption is that increased electrification of the heating and transport sectors and the introduction of large datacentres will change both the level and the hourly consumption profile considerably. The electrification of the heating and transport sectors and the growth of large datacentres is observed internationally and the expectation of considerable changes in the level and hourly profile of electricity is not an isolated Danish phenomenon. The electrification of the heating sector mainly increases the seasonal variation, electric vehicles will (dependent of the charging technology and consumer behaviour) be a key determinant of the aggregated hourly consumption profile, while large datacentres mainly affect the level of consumption. Concerning the spatial distribution, individual heat pumps and electric vehicles are distributed among all municipalities and therefore affect both the transmission and the distribution grids. Large datacentres are large point-customers mainly affecting total consumption and specific nodes in the overall transmission grid. That is, the paper demonstrates that in addition to changed level of consumption, energy system models and models used for grid planning need to consider significant future changes in the hourly consumption profile.

Hourly metering of the electricity consumption by individual customers is introduced in many countries, implying that a very large and detailed set of data is collected. However, published analyses using these data are rather limited. The data is collected for billing purposes and is generally not available to researchers. In addition, linking meters to individual customers is subject to privacy regulations and statistics for the consumption by aggregated categories of customers are difficult to obtain. Therefore, most published analyses use surveys including a limited number of customers. A recent review of articles applying smart meter data for consumer classifications is Tureczek and Nielsen [6]. The model presented in Andersen et al. [5] uses a sample of about 2000 representative customers covering all categories of customers in Denmark West. Using the same statistics including about 4500 representative customers covering both East and West Denmark, Andersen et al. [7] analyse consumption profiles for aggregate categories of Danish customers. Applying data from about 120.000 households in California, Kwac et al. [8] classify customers into segments with different consumption profiles and determine daily profiles for types of days and climate zones. Using hourly data for 2008 from 3989 small customers in Finland, Räsänen et al. [9] develop consumption profiles for 10 categories of customers, e.g., detached houses or flats with and without electric heating, including both households and small service providers. Looking at Canadian data, Poulin et al. [10] analyse a random sample of 332 Hydro-Québec customers and develop a load-duration-curve for categories of customers. Coke and Tsao [11] analyse hourly consumption data for 923 British Columbia Hydro customers for a year starting 1. april 2004 and cluster these into 7 categories of customers covering both residential and industrial customers. Applying data from 221 households in Oshawa, (Ontario, Canada) Ndiaye and Gabriel [12] identify 9 parameters that determine the electricity consumption of households, e.g., the number of occupants in the house, whether the house is owned or rented, and the type of space heating system of the house. Analysing hourly consumption from about 1000 Portuguese low voltage customers, Figaldo et al. [13] develop hourly consumption profiles for customer categories defining standard profiles for low voltage customers not having hourly metering. Analysing 3622 residential customers in Ireland, Haben et al. [14] identify 10 groups of customers and show that the clustering is reliable. Analysing 1550 households in Norway Kipping and Trømborg [15] assess the impact of different heating systems on the level and hourly electricity consumption. They show that the main difference in the level of consumption is due to the use of direct electric heating, heat pumps or non-electric heating, while differences in the daily profile depend of whether the hot water is electric heated or not. Finally applying consumption profiles for Dutch households and service sector profiles from reference building data published by U.S. DOE, Voulis et al. [16] develop aggregated consumption profiles for approximately 15000 local areas in the Netherlands.

Another group of literature analysing hourly consumption profiles starts from bottom-up technical analyses of the use of household appliances. These analyses often focus on demand flexibility changing the aggregated consumption profile. Paatero and Lund [17] analyse residential customers in Finland and develop a model generating representative consumption profiles for categories of households assuming technical data for the availability and the use of household appliances. Widén et al. and Widén and Wäckelgård [18,19] combine technical data for appliances and time-use statistics from Sweden to generate profiles for groups of households and analyse how changing appliance efficiency and consumer behaviour may affect the aggregated consumption profile. Looking at consumption profiles for specific household appliances, Finn et al. [20] analyse dishwashers, Zehir and Bagriyank [21] focus on refrigerators, Dupont et al. [22] analyse flexibility from white goods and electric vehicles in Belgian and Love et al. [23] analyse the contribution of individual heat pumps to the load profile in Great Britain. Looking at Danish households Andersen et al. [24] analyse how different household appliances contribute to the aggregated consumption profile by households and how changing efficiencies of appliances affect future consumption and the hourly profile. A review of models for the generation of load curves for residential customers is presented in Grandjean et al. [25].

Looking at integration of renewable production and system flexibility Lund and Mathiesen [26] analyse a 100% renewable energy system and hourly flexibility provided by heat pumps, electric boilers, electrolyse and storage. Further analyses focusing on the integration of electricity and heating systems are presented in Mathiesen et al. [27] and the introduction new sources of flexibility such as solid, gaseous and liquid fuel storages, thermal storage and demand side flexibility from heat pumps and electric vehicles is analysed in Mathiesen et al. [28]. A model analysing the optimal management of the flexibility of electric vehicle batteries is presented in Li et al. [29], and a model for engaging consumers' flexibility in balancing services is given in Zotti et al. [30].

With respect to the aggregate demand in a market, numerous models forecasting short-, medium- and long-term consumption are published. In short-term forecasts, that is from 24 h up to a week ahead, variations in hourly consumption is important for production planning and market operation. To model systematic short-term variation in electricity consumption quite a number of different methods are used. Methods range from econometric models, time series models, models based on sine and cosine polynomials with different frequencies, to different formulations of splines and artificial - and fuzzy neural networks [31–40]. present examples of short-term models using different methods. Bunn et al. [31] compares different model set-ups for forecasting load, Ramanathan et al. [32] presents an econometric model analysing each hour of the day, that is they estimation an equation for each hour of the day going from hour 1 to hour 24. Amjady [33] presents a timeseries model estimation an ARIMA model for the Iranian electricity consumption. Manera and Marzullo [34] presents a Principal Component modelling of the load curves for Italy, France and Greece, respectively, and compare results to Fourier and

Constrained Smoothing Spline estimators. Aneiros et al. [35] presents a Principal Component model for daily load and prices in Spain. Dordonnat et al. [36] estimates a periodic stats space model of the French electricity load and Fan et al. [37] presents a semi-parametric model including temperature to forecast half-hourly loads in Australia. Moazzami et al. [38] proposes an Artificial Neural Network (ANN) model forecasting peak loads in the Iran National Grid and Lin and Chou [39] present a moving average and machine learning approach for short-term load forecasting of electricity demand in Taiwan. Kim and Cho [40] analyse a four year household data set form France and propose to combine convolutional neural network (CNN) and long short-term memory (LSTM) to describe/model the complex features of household consumption.

In the medium-term, up to a year, the seasonal variation becomes important [41–44]. present different models modelling seasonal variation. Martín-Rodríguez and Cáceres-Hernández [41] present a model of the hourly Spanish electricity demand applying periodic cubic splines to describe seasonal and weekly variations. Pedregal and Trapero [42] presents a multi-rate model forecasting monthly consumption including seasonality and afterwards hourly consumption in each month. Both monthly and hourly variations are described by trends and periodic components of different frequencies. Yukseltan et al. [43] presents a model for Turkey estimating sinusoidal terms with yearly, weekly and daily frequencies. Modelling auto-regressive and moving average components Boroojenia et al. [44] propose a generalized technique for modelling electricity load data with different cycles of seasonality, e.g. daily, weekly, quarterly and annual components.

Long-term projections of consumption is relevant for investments in production and transmission capacities. Normally, long-term forecast models use annual observations and aim to capture causal effect of changes in income, production, prices etc. Concerning hourly consumption, as consumption profiles vary between categories of customers, mainly structural changes and new categories of customers are important. To combine the long-term development and hourly consumption, often annual consumption by categories of customers are taken form a model describing annual causal relations and the hourly consumption is modelled assuming constant hourly consumption profiles per customer category. Besides analyses in Refs. [4,6] very few articles on long-term projections of hourly electricity consumption are published. One example is Filik et al. [45]. They model consumption using three sub-models, all dependent on the time only: an annual model where consumption follows a second order polynomial of the week number, and weekly and hourly sub-models, each described by sine and cosine polynomials at different frequencies in time.

2. Data for the hourly electricity consumption

The Danish TSO "Energinet.dk" collects data from all electricity meters in Denmark and deliver the data to Statistics Denmark. All large and many small customers have hourly metering of their consumption and by 2020 all customers shall have hourly meters. The present analysis uses data for 2015 where all large customers (with an annual consumption above 100.000 kWh.) and about 15% of small customers have hourly meters. Grouping customers into categories and municipalities, for each of the 98 municipalities, data for the hourly electricity consumption by aggregated categories of customers is calculated.

For week [46], 2015, Fig. 1 shows how aggregated categories of customers contribute to the total Danish consumption. Main observations from Fig. 1 are that the total consumption has a morning and an evening peak and that consumption is larger on workdays than on not workdays. In addition, production sectors mainly consume during daytime on workdays while households mainly consumes during the evening and in weekends. Another observation is that the category 'other sectors' is quite large. It has not been possible to ascribe customers in this category to a specific production sector. However, as we have specific municipal weights and profiles for this mixed category of customers, for the modelling the consequence is limited.

Looking at the seasonal variation, for 2015 Fig. 2 shows the average hourly consumption profile for individual months, for workdays and not workdays, for the total consumption and for consumption by categories of customers. Looking at total consumption the figure shows a considerable seasonal variation with a large consumption during the winter and a lower consumption during summer, and especially that the evening peak is reduced during summer. Households contribute considerably to the seasonal variation and especially to reducing the evening peak during summer. Agriculture has a morning and an afternoon peak in the winter and an almost constant consumption during summer. The difference between workdays and not workdays is limited. In general, agriculture is a minor electricity consumer in Denmark. Industry has a large consumption during workhours on workdays (7 a.m.–4 p.m.), many companies are closed on not workdays, and the consumption is almost the same all months. July is an exception where many industrial companies are closed for summer holidays 1–3 weeks. Comparing the private and public service sectors, the private service sector has a fairly long daily consumption profile, which stays at almost the same level across all months of the year, while the public service sector has a short daily consumption profile, a considerable seasonal variation and summer holidays in

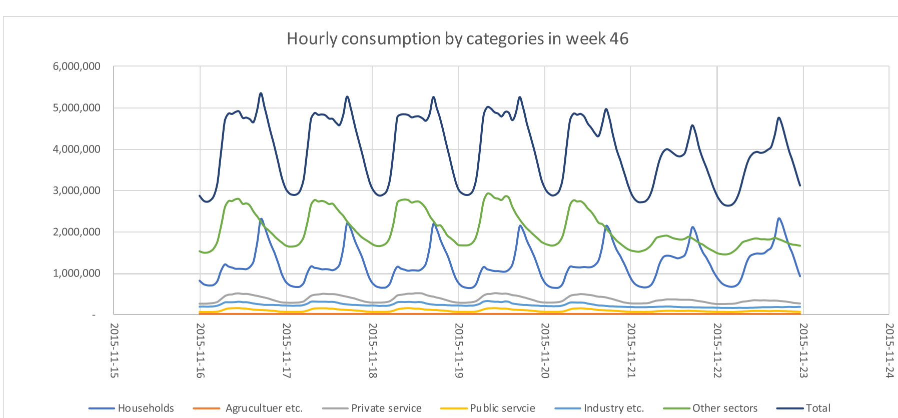

Fig. 1. Contribution by categories of customers to the aggregated Danish consumption in week 46, 2015.

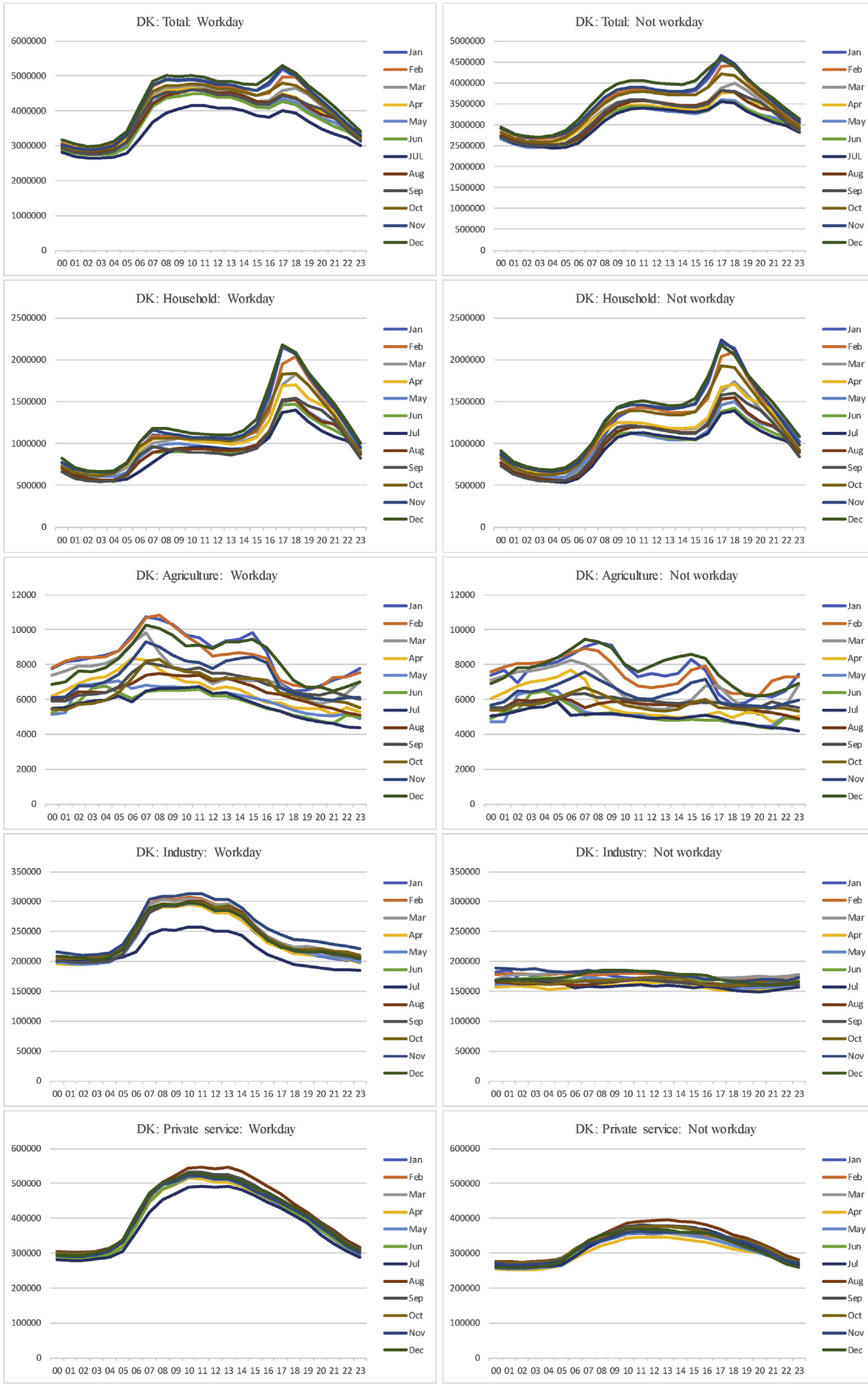

Fig. 2. Hourly consumption profiles for 2015.

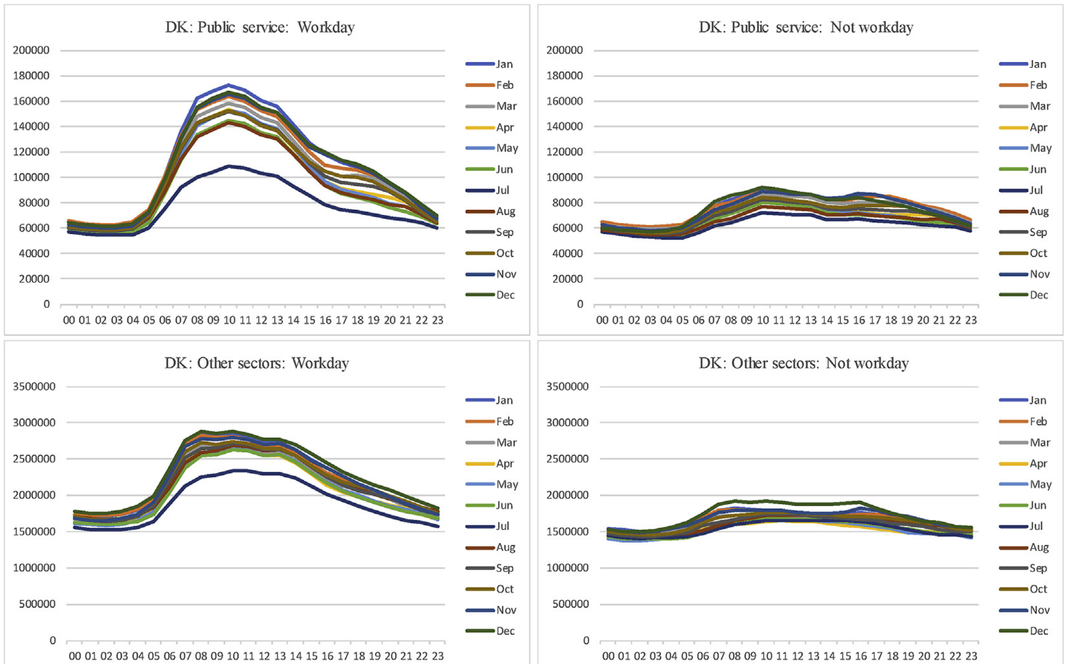

Fig. 2. (*continued*).

July. In addition, part of the private service sector is open on not workdays while most of the public service sector is closed. Finally looking at the category 'other sectors' the profile is a mix of industry, private - and public services. The profile has a limited seasonal variation except for the summer holidays in July. Comparing with statistics for the total annual electricity consumption we evaluated, that about 50% of the consumption within the category 'other sectors' is consumption within industry and about 25% is consumption in respectively the private and public service sectors.

To illustrate the spatial variation in consumption profiles, Fig. 3 shows the total and the industrial consumption profiles for three quite different municipalities. The aggregated consumption profiles differ between municipalities, both due to different weights and different profiles for categories of customers; especially the profile for industry varies between municipalities. For Copenhagen the profile reflects a large share of industry and services and that the daily profile for industry is very long. Furesø reflects a large share of households and some industry with a short daily profile. That is, the total consumption profile has a relatively large evening peak and a low consumption in July. For Kalundborg the total consumption has a limited daily variation and the industrial profile is dominated by a large company operating 24 h a day.

3. The model

To model hourly electricity consumption in a local area, the starting point is the identity that for each hour the consumption by categories of customers in an area adds up to the total consumption in the area. That is

$$\forall i: c_t^i = \sum_j c_t^{i,j} \tag{1}$$

where t is hours, i is municipalities in Denmark and j is the categories of customers: Households, Agriculture, Industry, Private services, Public services and Other sectors.[2]

As not all customers have hourly meters, the aggregate profile and the weight of customer categories within each municipality are calculated from secondary statistics. This implies that the sum of the hourly consumption over all customers and municipalities does not equal the aggregate hourly consumption in Denmark as reported by Nord Pool. To ensure that each hour the modelled consumption adds up to the aggregate consumption at Nord Pool, a residual variable defined in eq. (2) is constructed:

$$\forall t: c_t^{res} = c_t^{Nord\ Pool} - \sum_i c_t^i \tag{2}$$

where c_t^i is the calculated hourly consumption in municipality i, $c_t^{Nord\ Pool}$ is the aggregate national consumption at Nord Pool, and c_t^{res} is the "residual" consumption ensuring adding-up. Finally c_t^{res} is divided among municipalities according to the calculated annual consumption in each municipality. That is, as:

$$c_t^{i,res} = \left(\sum_t c_t^i \Big/ \sum_t \sum_i c_t^i \right) \cdot c_t^{res} \tag{3}$$

and the adjusted hourly consumption in each municipality $\ddot{c}_t^i$ is calculated as:

$$\ddot{c}_t^i = c_t^i + c_t^{i,res} \tag{4}$$

Using the model for baseline projections, it is assumed that:

The consumption profile per category and municipality is constant over time. That is, for each municipality the future hourly consumption profile for each consumer category is equal to the

[2] In this section, lower case letters refer to variables with an hourly resolution and upper case letters refer to annual variables.

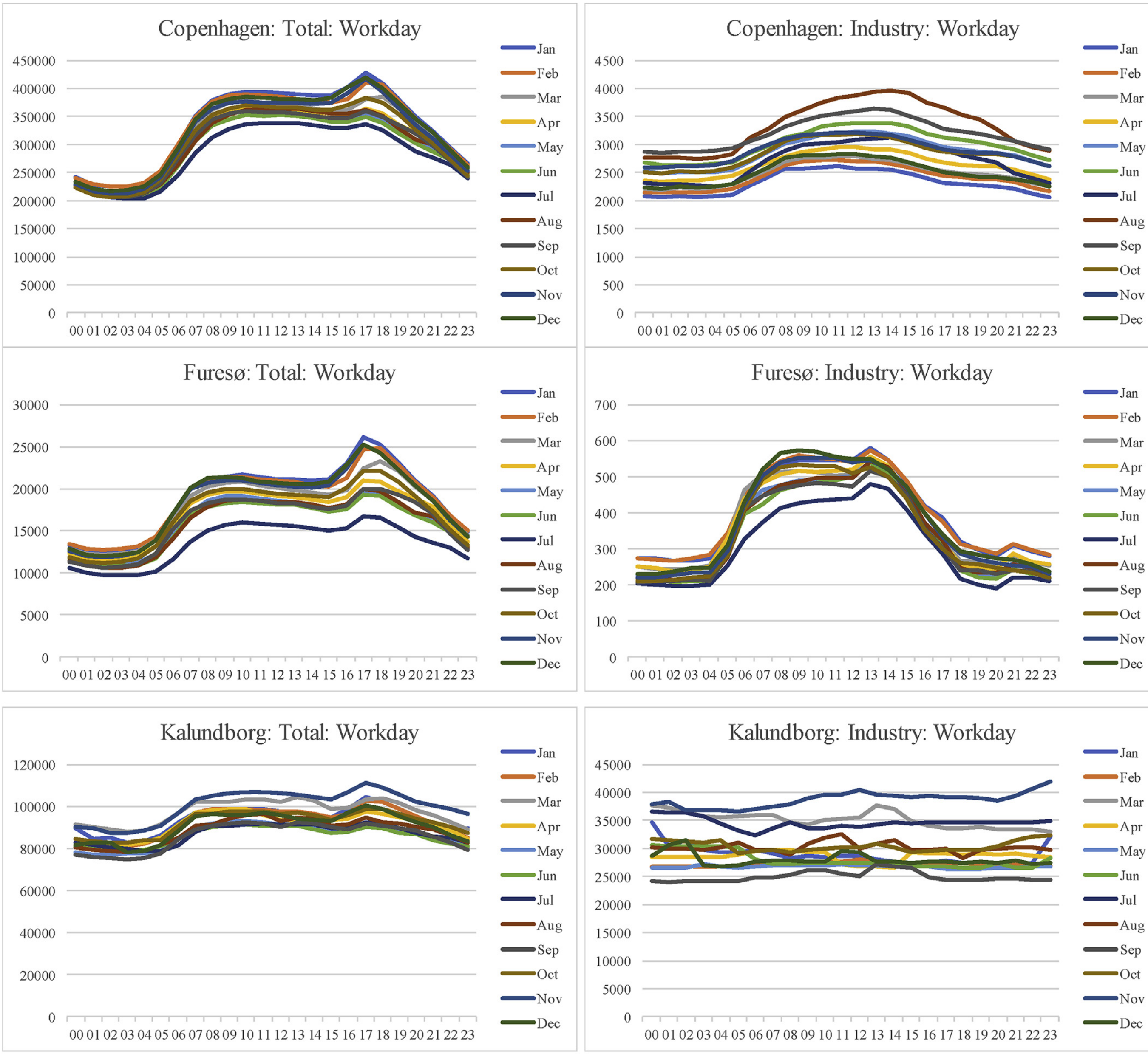

Fig. 3. The total and the industrial consumption profile for four municipalities.

profile in the base-year (B).

Each $c_t^{i,j}$ changes proportional to the annual change in national consumption of category j. That is:

$$c_t^{i,j}(T)\Big/c_t^{i,j}(B) = C^j(T)\Big/C^j(B) \quad or \quad c_t^{i,j}(T) = c_t^{i,j}(B)\cdot C^j(T)\Big/C^j(B) \tag{5}$$

where $C^j(T)$ is the national annual consumption by category j in the forecast-year T and $C^j(B)$ is the consumption in the base-year B.

The residual category ($c_t^{i,res}$) is projected to change proportional to the change in total electricity consumption.

New categories of consumption (e.g. electrical vehicles and individual heat pumps) are included in the projection with a specific hourly consumption profile that is identical for all municipalities. In addition, total consumption is divided among municipalities applying exogenous assumptions. That is:

$$c_t^{i,n}(T) = c_t^n \cdot C^{i,n}(T) \tag{6}$$

where c_t^n is the specified consumption profile for category n, adding to 1 over all hours of a year, and $C^{i,n}(T)$ is the annual consumption by category n in municipality i and year T.

Finally, for each municipality i, the projected hourly consumption in year T is calculated as:

$$\ddot{c}_t^i(T) = \sum_j c_t^{i,j}(T) + \sum_n c_t^{i,n}(T) \tag{7}$$

where j includes the classic - and the residual (res) categories of consumption, and n includes all new consumption categories.

That is, in a baseline projection profiles per category and

Table 1
A baseline projection of the annual electricity consumption in Denmark.

Classic consumption in GWh.	2018	2020	2025	2030	2040	Δ%2018–2025	Δ%2018–2040
Agriculture	1606	1519	1614	1684	1845	0.5	14.9
Industry	7809	7688	8433	8488	9113	8.0	16.7
Private service	7875	7607	7982	8151	8341	1.4	5.9
Public service	2281	2120	2041	2020	1909	−10.5	−16.3
Households	9535	9544	9900	10036	10076	3.8	5.7
Total	29106	28478	29970	30379	31284	3.0	7.5
New categories of consumption:						Δ%2018–2025 incl. new categories	Δ%2018–2040 incl. new categories
Individual heat pumps	1185	1337	1694	2266	3015	4.5	13.2
Electric vehicles and - busses	34	44	141	543	4315	4.9	27.3
Large data-centres	0	879	4727	7035	11432	20.5	65.0
Central heat pumps etc.	115	194	578	776	1524	21.9	69.4
Total	30440	30932	37110	40999	51570	21.9	69.4

municipality are assumed unchanged and the relative change in consumption per category is the same in all municipalities. This gives a first overall picture of expected changes in the aggregated consumption profiles. Alternative projections may assume changes in profiles per category and a different distribution of the national development e.g. a concentration of the industrial development or of new categories of consumption in specific regions/municipalities. Especially, looking at the development in a specific municipality the development of large companies in the municipality should be considered and if e.g. the municipality will have a relative large share of electric vehicles and/or individual heat pumps.

4. A baseline projection

To assess future changes in the aggregated consumption profile, the latest planning assumptions by the Danish TSO Energinet. dk [35] is used. Table 1 summarizes this projection.

Looking at the projection for categories of classic consumption, consumption within the public service sector is decreasing and consumption within industry is increasing. For private services and households consumption increases moderately.

Major changes are coming from new categories of consumption. Electrification of the transport and heating sectors increase electricity consumption in 2040 by about 20%. The absolute largest change in the electricity consumption comes from a number of large datacentres. This alone increases consumption in 2040 with 35% and large datacentres will consume an amount equal to all households in Denmark. Finally, central heat pumps and electric boilers are introduced in the district heating system partly acting as flexible customers. In 2040 central heat pumps and electric boilers will consume about 3% of the total electricity consumption. That is, in 2040 total electricity consumption will be 69% larger than today, classic consumption increases only 7.5% and more than half of the increase is ascribed to large datacentres.

Table 2
Change in maximum-, average- and minimum consumption within the classic categories of consumption.

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	2.86	2.86	3.22	3.70	4.28	5.17	6.67	7.26	8.56
The rest of Sealand	2.99	3.04	3.54	3.31	3.97	4.90	6.41	7.13	8.62
North Jutland	3.02	3.05	2.98	4.18	4.62	5.75	7.32	7.81	8.91
Central Jutland	3.15	3.03	3.45	4.16	4.53	5.00	7.44	7.70	8.62
Denmark South	2.57	2.98	3.44	4.38	4.47	5.00	7.06	7.59	8.61
Denmark West	3.02	3.01	3.46	4.03	4.53	5.02	7.17	7.68	8.65
Denmark East	2.91	2.92	3.33	3.56	4.17	5.08	6.58	7.22	8.58
Denmark	2.88	2.98	3.12	3.66	4.38	4.83	6.65	7.49	8.10

4.1. Classic consumption

Considering effects of changes in the classic consumption, for each municipality the projected change in minimum, average and maximum hourly consumption is reported in the supplementary data file, and a summary looking at regions in Denmark is shown in Table 2. A main observation from Table 2 is that classic consumption changes total electricity consumption only slightly, and that regional differences are minimal. The average and minimum consumption increases marginally more than the maximum/peak consumption. The explanation is that consumption by households (determining the evening peak) increases less than the

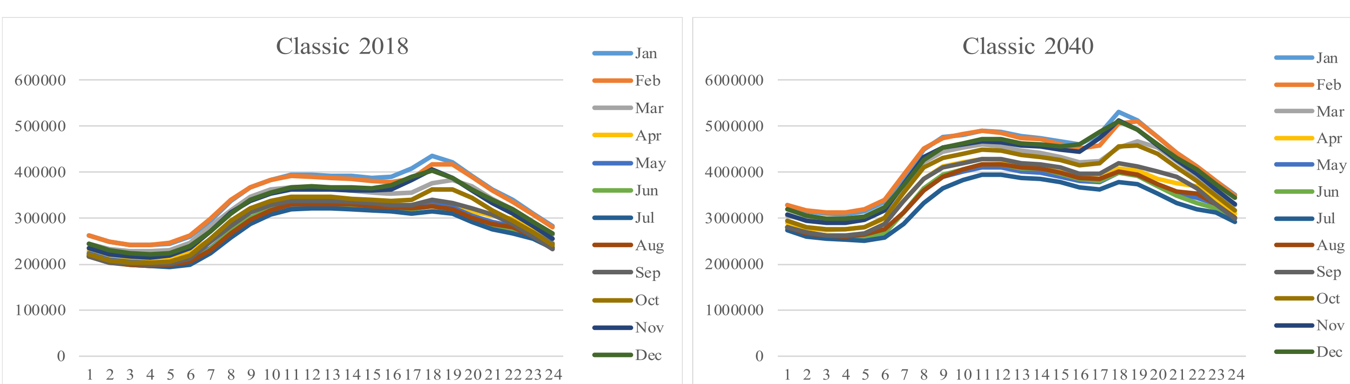

Fig. 5. Aggregate consumption profile for classic categories of consumption in 2018 and 2040.

Table 3
The share of households and individual heat pumps in Danish regions.

Region/DK	The Copenhagen area	The rest of Sealand	Denmark South	Central Jutland	North Jutland	Denmark West	Denmark East	Denmark
	0.314	0.144	0.214	0.223	0.105	0.542	0.458	1.000

consumption by industry (contributing mainly to the day-time peak), and the evening peak remains the absolute peak. Looking at municipalities, Table A2 in the data file shows a slightly larger variation between municipalities than between regions, but still changes are quite limited. The municipality with the lowest increase in consumption is Herlev where about 30% of the total electricity consumption is within the public service sector (Table 1 shows that consumption in the public service sector decreases). Looking at changes in the aggregated consumption profile, Fig. 5 shows the profile in the base-year 2018 and in 2040. Comparing the profiles confirms that the classic consumption will change the aggregated consumption profile only marginally.

4.2. Individual heat pumps

Table 1 shows that consumption by individual heat pumps increases from 1185 GWh. in 2018–3015 GWh. in 2040. This is equivalent to an increase in the number of individual heat pumps from about 300.000 in 2018 to about 1.000.000 in 2040, or that about 1/3 of all Danish households will have a heat pump in 2040. As a first quick assumption giving a preliminary “baseline-estimation” of regional effects the heat pumps are divided among municipalities according to the number of households. Clearly this is a very simple assumption and in further work the regional distribution should take into account e.g. district heating areas or other regional issues affecting the introduction of individual heat pumps. However, due to lack of specific information and just for illustration purposes, the simple distribution according to the number of households is chosen in this paper. Table 3 shows the share ascribed to each region.

The hourly consumption profile for heat pumps is calculated from statistics for single-family houses with and without electric heating, respectively. This profile represents an average heating profile in a normal year, and will under-estimate the peak demand under extreme weather conditions. How large the under-estimation is depends on the capacity of the installed heat pumps, and although installed heat pumps may have a capacity larger than required for the peak demand in a normal year, probably they will not have the capacity to cover a 10 years incident. In addition, many studies argues that individual heat pumps may supply demand side flexibility and thereby change the hourly consumption profile. In the present calculations the consumption profile is assumed to be constant excluding possible effects from demand side flexibility. However, alternative calculations may include external evaluations of demand flexibility changing the daily profile but maintaining a considerable seasonal variation in the consumption.

Normalized to one over the year, Fig. 6 shows the calculated profile for a normal year. The main characteristics of the profile is a very large seasonal variation; consumption is high during winter

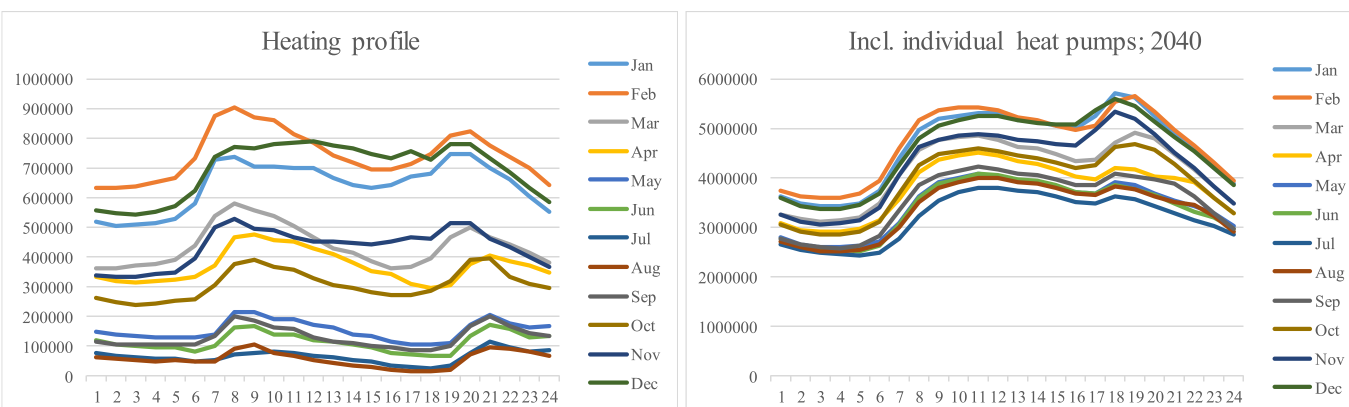

Fig. 6. The heating profile and the aggregated consumption profile incl. individual heat pumps 2040.

Table 4
Change in consumption including individual heat pumps.

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	5.13	4.75	3.74	9.41	9.02	6.46	15.03	14.20	10.44
The rest of sealand	4.92	4.61	3.99	8.21	7.96	6.03	13.53	12.94	10.25
Jutland, North	4.89	4.36	3.38	8.89	7.91	6.76	14.21	12.62	10.38
Jutland, Central	5.27	4.49	3.63	9.50	8.22	5.87	15.27	13.09	9.71
Denmark, South	4.97	4.40	3.53	10.17	8.06	5.61	15.65	12.82	9.34
Denmark West	5.10	4.43	4.63	9.27	8.09	6.15	14.84	12.88	11.07
Denmark East	5.05	4.70	3.82	8.99	8.65	6.31	14.50	13.75	10.38
Denmark	4.87	4.54	3.53	9.17	8.32	5.87	14.49	13.23	9.61

Table 5
Share of vehicles in regions, 1/1–2017.

	The Copenhagen area	The rest of Sealand	Denmark South	Central Jutland	North Jutland	Denmark West	Denmark East	Denmark
Region/DK	0.277	0.151	0.225	0.240	0.107	0.571	0.428	1.00

and very low during the summer, and the daily profile has a small morning and evening peak which is mainly related to the consumption of hot water.

Including the expected development in consumption by individual heat pumps Table A4 in the data file shows the changes in the maximum, average and minimum consumption in each municipality, and Table 4 shows a summary of changes in Danish regions. In addition, Fig. 6 shows the aggregated consumption profile in 2040 including consumption by individual heat pumps. The main conclusion from Table 4 is that consumption in the hour with maximum consumption increase more than consumption in the average and especially the minimum consumption hour. Further, comparing Figs. 5 and 6 we observe that especially the seasonal variation increases by the inclusion of individual heat pumps. That is, individual heat pumps mainly contribute to the consumption during the winter, where consumption is already high. In addition, individual heat pumps add especially to the morning and evening peaks where the consumption is high.

Looking at individual municipalities in Table A4 in the data file we observe some variation in the change in different municipalities

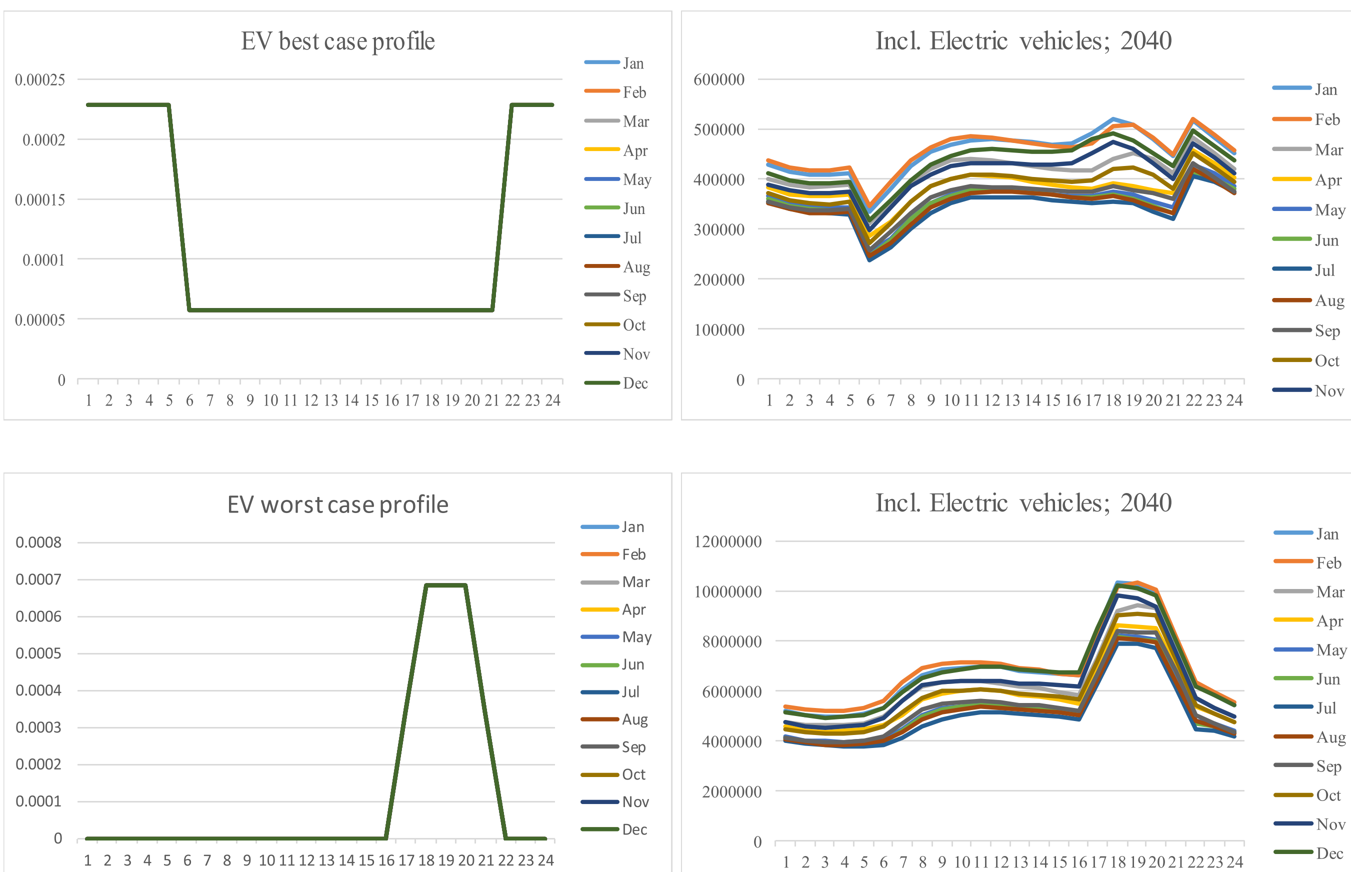

Fig. 7. EV profiles and the aggregated consumption profile incl. EVs.

Table 6
Change in consumption incl. electric vehicle. (EV profile: best case charging).

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	5.24	5.12	5.05	13.67	22.90	18.95	19.63	29.19	24.96
The rest of Sealand	5.03	4.98	4.85	12.52	21.79	18.32	18.18	27.85	24.06
Jutland, North	4.98	4.66	4.45	12.42	19.09	21.75	18.02	24.64	27.17
Jutland, Central	5.38	4.84	3.86	13.73	21.39	18.27	19.84	27.27	22.84
Denmark, South	5.08	4.74	4.09	14.21	20.60	17.04	20.01	26.32	21.83
Denmark West	5.21	4.76	4.95	13.34	20.60	17.04	19.24	26.35	22.83
Denmark East	5.17	5.07	5.15	13.27	22.51	18.77	19.12	28.72	24.89
Denmark	4.98	4.89	3.83	13.42	21.37	17.55	19.07	27.30	22.06

Table 7
Change in consumption incl. electric vehicle. (EV profile: worst case charging).

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	6.48	5.12	3.74	59.72	22.90	6.46	70.07	29.19	10.44
The rest of Sealand	6.29	4.98	3.99	59.18	21.79	6.03	69.18	27.85	10.25
Jutland, North	6.01	4.66	3.38	50.75	19.09	6.76	59.82	24.64	10.38
Jutland, Central	6.61	4.84	3.63	59.38	21.39	5.87	69.92	27.27	9.71
Denmark, South	5.43	4.74	3.53	57.05	20.60	5.61	65.58	26.32	9.34
Denmark West	6.39	4.76	4.63	57.33	20.60	6.15	67.39	26.35	11.07
Denmark East	6.42	5.07	3.82	59.53	22.51	6.31	69.76	28.72	10.38
Denmark	6.22	4.89	3.53	59.34	21.37	5.87	69.26	27.30	9.61

Table 8
Change in consumption incl. large datacenters and best case charging of electric vehicle.

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	5.24	5.12	5.05	13.67	22.90	18.95	19.63	29.19	24.96
The rest of Sealand	5.03	4.98	4.85	12.52	21.79	18.32	18.18	27.85	24.06
Jutland, North	4.98	4.66	4.45	12.42	19.09	21.75	18.02	24.64	27.17
Jutland, Central	11.84	14.85	22.53	34.55	52.17	72.56	50.48	74.77	111.44
Denmark, South	41.37	60.94	104.26	36.19	48.27	57.64	92.54	138.62	221.98
Denmark West	22.23	30.83	51.66	31.23	44.75	55.48	60.41	89.38	135.80
Denmark East	5.17	5.07	5.15	13.27	22.51	18.77	19.12	28.72	24.89
Denmark	15.13	20.45	31.38	24.73	36.94	43.62	43.60	64.95	88.69

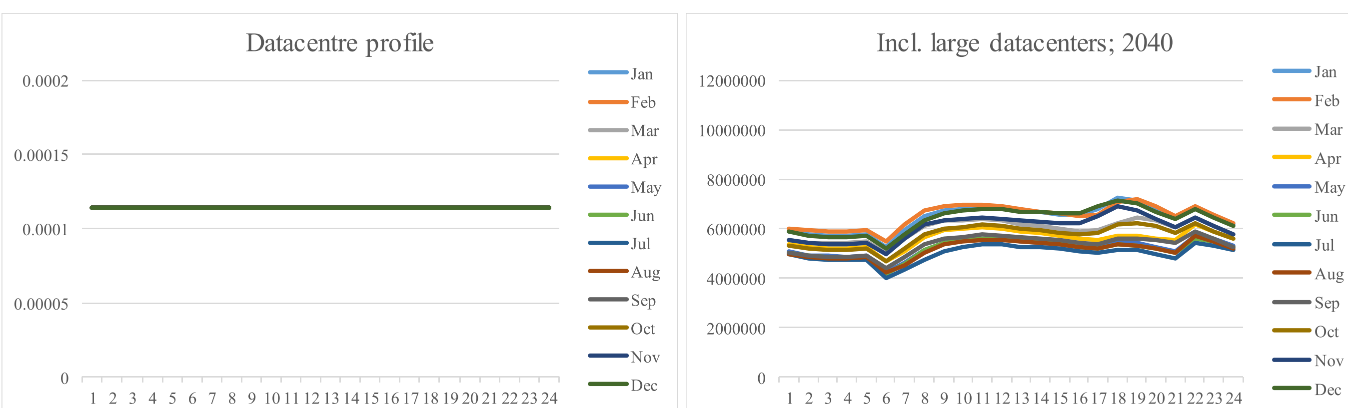

Fig. 8. Consumption profile incl. large datacenters and best case charging of electric vehicles in 2040.

and especially for a few municipalities that consumption in the average and minimum hour increases more than in the peak hour. For these municipalities typically the present peak is a daytime peak (and not the evening peak) and individual heat pumps contribute less to the daytime consumption. In a few municipalities the effect of the heat pumps is that the absolute peak changes from a daytime peak to an evening peak.

4.3. Electric vehicles

The baseline projection in Table 1 shows a moderate increase in the consumption by electric vehicles and busses until 2025. However, the transformation from conventional to electric vehicles (EVs) is accelerated from 2030 to 2040 and in 2040 there will be around 1.5 mill electric vehicles in Denmark. That is, in 2040 about 55% of all vehicles in Denmark will be EVs. In the model, consumption by EVs is distributed among municipalities according to the stock of vehicles. Table A5 in the data file shows the present share of vehicles in each municipality and Table 5 shows the share of vehicles in regions.

The charging profile for EVs depend on both the technology and behavior of vehicle owners. Observed charging profiles for individual EVs are few, and often EVs are charged several places e.g. at home, at work, at public charging stations and at fast charge stations. The distribution of charging between places is difficult to assess. However, a survey form Norway [47] shows that for daily use about 90% are charging at home, about 40% often charge at work and about 20% regularly use public charging stations. For daily charging, fast charge stations are rarely used. The place of charging is important as the hour of charging correlates with the place. At home, the EV is charged in the evening and during the night, at work it is charged during work hours (mainly in the morning) and

Table 9
Change in consumption incl. central heat pumps and best case charging of electric vehicle.

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
The Copenhagen area	5.24	6.05	5.31	13.67	28.78	20.36	19.63	36.58	26.75
The rest of Sealand	5.03	5.03	4.87	12.52	22.23	18.43	18.18	28.38	24.19
Jutland, North	4.98	7.56	5.35	12.42	21.18	22.00	18.02	30.35	28.53
Jutland, Central	11.84	17.22	23.13	34.55	52.88	72.61	50.48	79.20	112.53
Denmark, South	41.37	62.23	104.56	36.19	48.68	57.70	92.54	141.21	222.59
Denmark West	22.23	32.86	51.78	31.23	45.50	55.60	60.41	93.31	136.17
Denmark East	5.17	5.69	5.33	13.27	26.49	19.73	19.12	33.69	26.10
Denmark	15.13	21.93	31.76	24.73	38.87	44.06	43.60	69.33	89.82

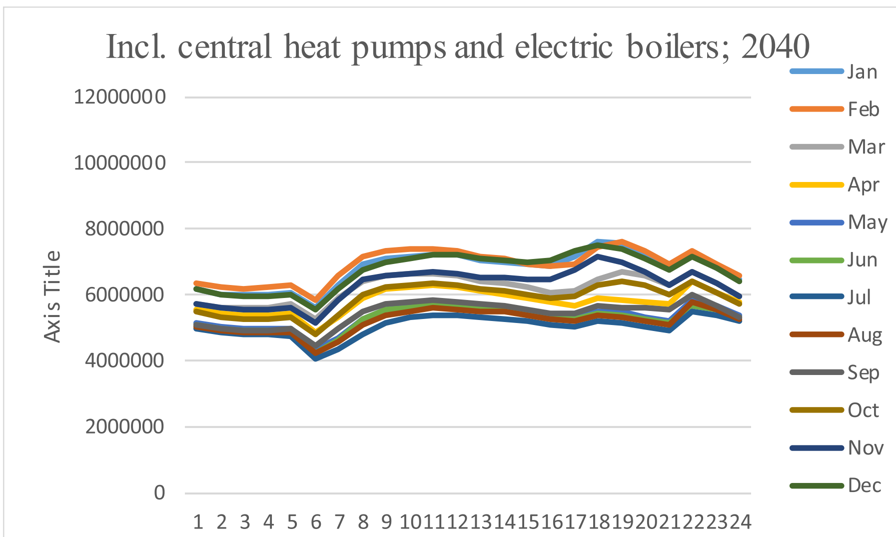

Fig. 9. Consumption profile incl. central heat pumps and best case charging of electric vehicles.

charging at public stations are distributed over most of the day and evening.

Looking at the length and peak of charging the technology becomes important. Assuming an average EV with an efficiency of 0.2 kWh/km driving 50 km per day, the daily charging required is 10 kWh. With a standard electric switch in Danish households (220 V and 10 Amp) the charge is 2.2 kWh/h and it will take approximately 5 h to charge the EV. For a large EV with a battery capacity of 85 kWh a full charging will take around 37 h. Shifting to a 16 Amp fuse the charging rate increases to 3.5 kWh/h and the time for daily charging is reduced to about 3 h. At work the fuse may be 32 Amp and the switch a 2 or 3 phase switch delivering effects of 7.3 and 11.5 kW, respectively. A fast charge stations may deliver effects of more than 50 kW. That is, the different technologies imply different effect requirements and different charging profiles.

As information concerning the present charging profile for EVs is limited and the profile may change considerably in the future e.g. due to charging technology and incentive schemes targeting EVs to provide demand flexibility, to illustrate effects of adopting EVs in this paper calculations are based on two extreme charging profiles. In the best case vehicles are mainly charged during the night between 9 p.m. and 5 a.m. illustrating a case where EVs have a minimal effect on peak load. In the worst case owners start charging the vehicle when they come home after work. That is, EVs are charged 4 h from 5.30 to 9.30 p.m. implying a max. addition to the peak load. Fig. 7 shows the two profiles and the effect on the aggregated consumption profile in 2040 and Tables 6 and 7 show the consequences of including electric vehicles with respectively the best case and worst case charging profile.

Looking at the tables (comparing with results in Table 4), as the adoption of EVs is limited in 2025, for both the best and worst case charging, changes in max./average/min. consumption are limited. However, looking at 2040, where about 55% of all vehicles are electric, the effect of the charging profile is considerable. In the worst case scenario, the maximum consumption in the different regions increases between 60% and 70%, with the largest increase in the Copenhagen area. Due to the assumed consumption profile in the worst case, where EVs are charged from 5.30 to 9.30 p.m. the minimum consumption is not affected as the observed minimum consumption is during the night (the change in the minimum consumption is the same in Tables 4 and 7).

In the best case the max./average/min. consumption increase in the same order of magnitude and especially the increase in the maximum consumption from 2018 to 2040 is about 20%, only. Comparing with Table 4, in the best case EVs add only 5% to the maximum consumption. That is, as shown in Fig. 7 the charging profile for EVs is very important for the required peak capacity and the aggregate consumption profile. In the worst case EVs may provide considerable challenges for the energy system and both transmission and distribution grids, while in the best case the contribution to the peak load is minimal. In addition, other analyses indicate that possible flexibilities in charging EVs actually may contribute to solve part of the short-term problems in the system and grids. See e.g. Juul et al. [48] and Gunkel [49].

4.4. Large datacenters

Hyper scale datacentres may be placed anywhere having access to sufficient optic fibre net and a secure electricity supply. At present, the Danish TSO is connecting the first large datacentres, and in the baseline scenario (Table 1) further large datacentres are expected to be placed in the western part of Denmark. According to the baseline projection, in 2040 large datacentres will consume electricity equal to 1/3 of the classic consumption or as much as all Danish households. Contrary to most other customers in Denmark, large datacentres are very large point consumers. Typically, a datacentre is placed close to the overall transmission grid and has its own transformer station. That is, large datacentres are connected almost directly to the transmission grid and have a limited effect on the local distribution grid.

In the model, as a first approximation the consumption profile for large datacentres is assumed to be uniform over all hours of the year. This may not be entirely correct, but it is evaluated that the daily and seasonal variations caused by variations in computer processing and the outdoor temperature are relatively small.

Table 8 shows the results of including large datacentres. Comparing with Table 6, as the datacentres are placed in central Jutland and Denmark South, for the other regions figures in Tables 6 and 8 are identical. For Denmark South the maximum consumption in 2040 is about twice the peak in 2018, and the change in the minimum consumption is about 200%. That is, relatively the consumption profile is getting flatter, but as seen comparing Figs. 7 and 8, the profile is unchanged except for a shift in the level.

4.5. Central heat pumps and electric boilers

Some of the district heat distributers have large heat pumps and a few have electric boilers contributing to the production of district heat when the electricity price is favorable. That is, when the electricity price is very high, the heat is produced using other energy sources. However, as the investment costs especially for central heat pumps are relatively high, central heat pumps have a reasonable high load-time. Therefore, in the model, we include the central heat pumps and electric boilers with a standard heating profile, but assume, that in the peak-hour none of the units produce. That is, central heat pumps and electric boilers are included in the minimum and average consumption using a standard heating profile (shown in Fig. 6), but they do not contribute to the maximum consumption. This is a very simple way to account for one aspect of the flexibility supplied by central heat pumps and electric boilers, but clearly, this does not give the full credit to the flexibility of these technologies.

Looking at Table 9, the average consumption in 2040 increases by about 5% more than in Table 8, and if the peak consumption was allowed to increase according to the heating profile the maximum consumption would have increased slightly more. The minimum consumption changes only marginally. Looking at Fig. 9 it is noticed that the seasonal variation is slightly larger than in Fig. 8, but in general the difference is minor. That is, the demand flexibility of

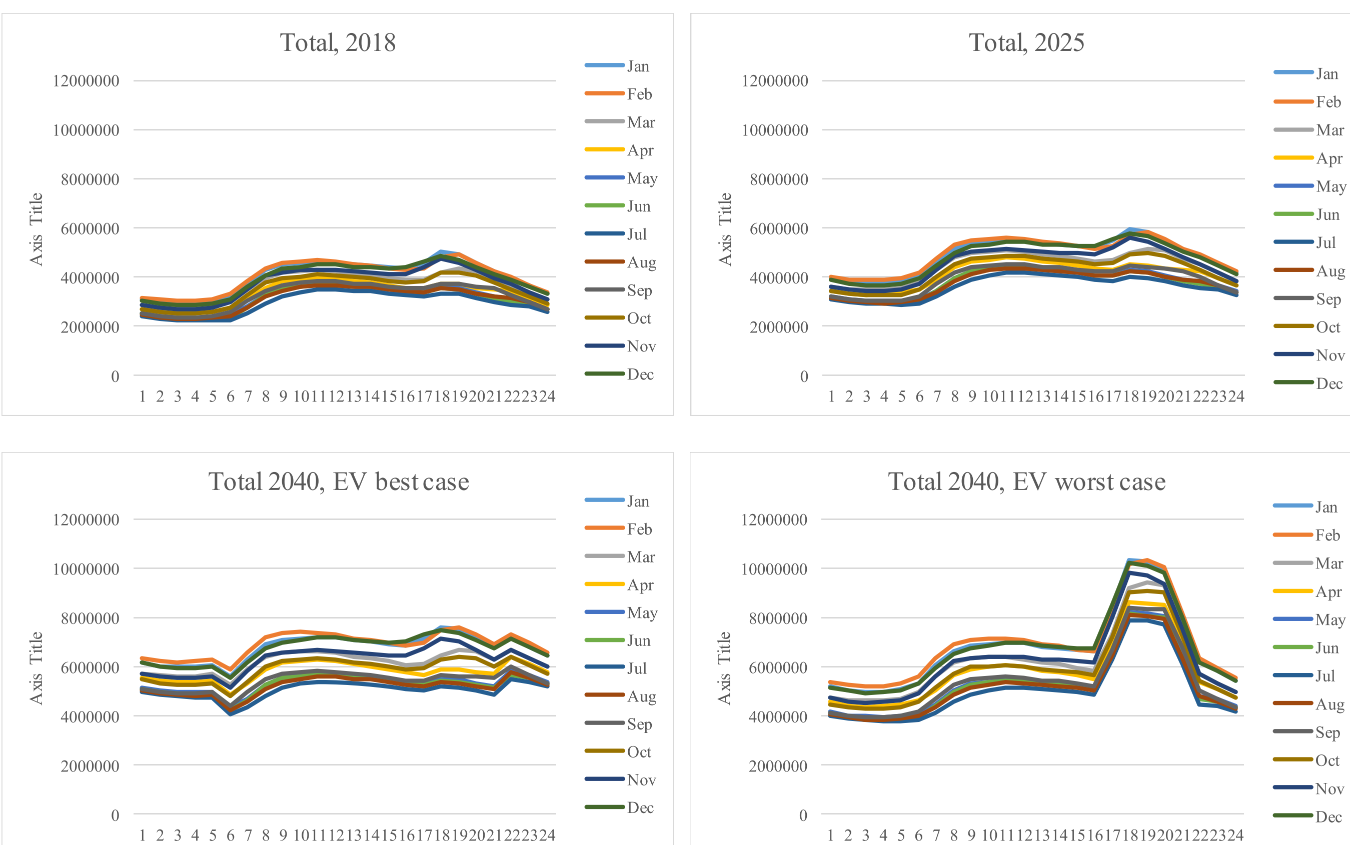

Fig. 10. Consumption profile 2018, 2025 and 2040 including all consumer segments.

Table 10
Change in national consumption including changes in different consumer segments.

	% change 2018–2025			% change 2025–2040			% change 2018–2040		
	max	avg	min	max	avg	min	max	avg	min
Classic consumption	2.88	2.98	3.12	3.66	4.38	4.83	6.65	7.49	8.10
Incl. individual heat pumps	4.87	4.54	3.53	9.17	8.32	5.87	14.49	13.23	9.61
Incl. electric vehicles worst	6.22	4.89	3.53	59.34	21.37	5.87	69.26	27.30	9.61
Incl. electric vehicles best	4.98	4.89	3.83	13.42	21.37	17.55	19.07	27.30	22.06
Incl. datacentres	15.13	20.45	31.38	24.73	36.94	43.62	43.60	64.95	88.69
Incl. large heat pumps	15.13	21.93	31.76	24.73	38.87	44.06	43.60	69.33	89.82
Incl. large heat pumps, EV worst	18.22	21.93	31.48	69.23	38.87	34.96	100.06	69.33	77.45

these technologies may contribute to the integration of renewable production technologies with a volatile, intermettent and only partly predictable production without adding to the required peak capacity in the system and grids.

5. Summary and conclusions

The Danish TSO (Energinet.dk) collects data from all hourly meters and delivers the data to Statistics Denmark. Aggregating the data into customer categories and municipalities, a model projecting the hourly consumption in municipalities is developed. Using the latest projection of the annual electricity consumption applied in the planning by Energinet. dk, Table 10 shows a baseline projection of changes in the aggregate max./average/min. consumption and Fig. 10 shows how the aggregated consumption profile may change.

A few main conclusions from Table 10 are:

- The classic consumption will change marginally increasing minimum consumption slightly more than the peak consumption.
- New categories of consumption will contribute significantly to the total consumption, especially after 2025, and the different new categories of consumption will affect the energy system and the grid quite differently.
- Individual heat pumps will mainly increase consumption during the winter and increase the peak consumption. As we use a consumption profile calculated for a normal year, under extreme weather conditions we may under-estimate the peak demand. The consumption is distributed among all municipalities.
- Electric vehicles will primarily affect consumption after 2025. In the long-term the charging profile for electric vehicles will be a key determinant of the aggregate consumption profile, determining the required production and grid capacities. Key issues will be the choice of charging technology and the utilization of the demand flexibility of EVs.
- Large datacentres will increase consumption significantly both before and after 2025 and will contribute to the consumption profile by adding almost a constant at all hours. That is, looking at relative effects large datacentres will mainly contribute to the minimum consumption. As large datacentres are point customers, they will affect the energy system and the transmission grid at specific nodes, but will have a limited effect on local distribution grids. In the baseline projection, all large datacentres are placed in Denmark West.
- Central heat pumps and electric boilers are flexible customers that may assist the integration of volatile renewable production technologies without increasing the demand for peak capacities in the system and grids.
- In the worst case EV charging, the peak consumption increases 100% from 2018 to 2040, but if EVs are charged off peak, the change in peak consumption will be more than halved.

Comparing consumption profiles in Fig. 10, in 2025 the daily consumption profile has changed marginally, but the seasonal variation is increased. In 2040, the aggregate profile is mainly determined by the charging profile for EVs. In Fig. 10 (bottom left) EVs are charged during the night flattening the daily consumption profile, while in Fig. 10 (bottom right) EVs are charged after work from 5.30 p.m. and in this case determine the peak consumption.

Finally, considering regional variations, individual heat pumps and electric vehicles are located in regions more or less proportional to the population (according to the number of households and the number of vehicles today). Large data centres are point customers affecting specific grid nodes, all in the western part of Denmark. That is, looking at Table 9 for the best case charging of EVs and including large data centres, from 2018 to 2040 peak consumption increases 90% in Denmark South but only 18% in the Northern part of Jutland.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2019.115890.

References

[1] Lund H. Renewable energy systems. In: A smart energy systems approach to the choice and modeling of 100% renewable solutions, eBook. second ed., ISBN 9780124095953. https://www.elsevier.com/books/renewable-energy-systems/lund/978-0-12-410423-5. https://www.energyplan.eu/.

[2] Wiese F, Bramstoft R, Koduvere H, Alonso AP, Balyk O, Kirkerud JG, Tveten ÅG, Bolkesjø TF, Münster M, Ravn H. Balmorel open source energy system model. Energy Strategy Reviews; 2018. p. 26–34. http://orbit.dtu.dk/files/143614670/1_s2.0_S2211467X18300038_main.pdf.

[3] IEA-ETSAP TIMES model. https://www.climatesmartplanning.org/dataset/times-integrated-markalefom-system-energy-planning-modeling-platform.html.

[4] Connolly, D., Lund, H., Mathiesen, B.V., Leahy, M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied Energy; 2010. p. 1059–82. https://ac.els-cdn.com/S0306261909004188/1-s2.0-S0306261909004188-main.pdf?_tid=b6a76cc8-8c34-4b4e-b848-3be446ddb93f&acdnat=1551256707_d2a5ac68b425b1222b32f897104dec17.

[5] Andersen FM, Larsen HV, Juul N, Gaardestrup RB. Differentiated long term projections of the hourly electricity consumption in local areas. The case of Denmark West. Appl Energy 2014;135(15 December):523–38. https://www.sciencedirect.com/science/article/pii/S0306261914008861.

[6] Alexander Martin Tureczek, Per Sieverts Nielsen. Structured literature review of electricity consumption classification using smart meter data. https://www.mdpi.com/search?q=Tureczek&authors=&journal=energies&article_type=&search=Search.

[7] Andresen FM, Larsen HV, Boomsma TK. Long-trem forecasting of hourly electricity load: identification of consumption profiles and segments of customers. Energy Convers Manag 2013;68:244–52. https://www.sciencedirect.com/science/article/pii/S0196890413000381.

[8] Kwac J, Flora J, Rajagopal R. Household energy consumption segmentation

using hourly data. IEEE TRANSACTIONS ON SMART GRID JANUARY 2014;5(NO. 1). https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6693793.
[9] Räsänen T, Voukantsis D, Niska H, Karatzas K, Kolehmainen M. Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data. Appl Energy 2010;87:3538–45. https://ac.els-cdn.com/S0306261910001832/1-s2.0-S0306261910001832-ain.pdf?_tid=29eb5219-eb5f-4457-b506-915fbe8d9407&acdnat=1538640535_a1f6a369df13eec874774890043bb747.
[10] Poulin A, Dostie M, Fournier M, Sansregret S. Load duration curve: a tool for technico-economic analysis of energy solutions. Energy Build 2008;40:29–35. https://www.researchgate.net/publication/245196831_Load_duration_curve_A_tool_for_technico-economic_analysis_of_energy_solutions.
[11] G. Coke, M. Tsao. Random effects mixture models for clustering electrical load series. J Time Ser Anal 31(6):451-464. https://www.researchgate.net/publication/227376027_Random_effects_mixture_models_for_clustering_electrical_load_series
[12] Ndiaye D, Gabriel K. Principal component analysis of the electricity consumption in residential dwellings. Energy Build 2011;43:446–53. https://www.sciencedirect.com/science/article/pii/S0378778810003592.
[13] Fidalgo JN, Matos MA, Riberio L. A new clustering algorithm for load profiling based on billing data. Electr Power Syst Res 2012;82:27–33. 2012, https://www.sciencedirect.com/science/article/pii/S0378779611002033.
[14] Haben S, Singleton C, Grindrod P. Analysis and clustering of residential customers energy behavioral demand using smart meter data. IEEE TRANSACTIONS ON SMART GRID JANUARY 2016;7(NO. 1). https://ieeexplore.ieee.org/document/7063233.
[15] Kipping A, Trømborg E. Hourly electricity consumption in Norwegian households - assessing the impact of different heating systems. Energy; 2015. p. 655–71. https://www.sciencedirect.com/science/article/pii/S0360544215012050.
[16] Voulis N, Warnier M, Brazier FMT. Understanding spatio-temporal electricity demand at different urban scales: a data-driven approach. Appl Energy 2018;230:1157–71. https://www.sciencedirect.com/science/article/pii/S0306261918312959.
[17] Paatero JV, Lund PD. A model for generating household electricity load profiles. Int J Energy Res 2006;30(5):273–90. https://onlinelibrary.wiley.com/doi/abs/10.1002/er.1136.
[18] Widén J, Lundh M, Vassileva I, Dahlquist E, Ellegård K, Wäckelgård E. Constructing load profiles for household electricity and hot water from time-use data-Modelling approach and validation. Energy Build 2009;41(7):753–68. https://www.sciencedirect.com/science/article/pii/S0378778809000413.
[19] Widén J, Wäckelgård E. A high-resolution stochastic model of domestic activity patterns and electricity demand. Appl Energy 2010;87(6):1880–92. https://www.researchgate.net/publication/223477044_A_high-resolution_stochastic_model_of_domestic_activity_patterns_and_electricity_demand.
[20] Finn P, O'Connell M, Fitzpatrick C. Demand side management of a domestic dishwasher: wind energy gains, financial savings and peak-time load reduction. Appl Energy 2013;101:678–85. https://www.sciencedirect.com/science/article/pii/S0306261912005156.
[21] Zehir MA, Bagriyanik M. Demand Side Management by controlling refrigerators and its effects on consumers. Energy Convers Manag 2012;64:238–44. https://www.sciencedirect.com/science/article/pii/S019689041200218X.
[22] Dupont B, Dietrich K, De Jonghe C, Ramos A, Belmans R. Impact of residential demand response on power system operation: a Belgian case study. Appl Energy 2014;122:1–10. https://www.sciencedirect.com/science/article/pii/S0306261914001585.
[23] Love J, Smith AZP, Watson S, Oikonomou E, Summerfield A, Gleeson C, Biddulph P, Chiu LF, Wingfield J, Martin C, Stone A, Lowe R. The addition of heat pump electricity load profiles to GB electricity demand: evidence from a heat pump field trial. Appl Energy 2017;204:332–42. https://reader.elsevier.com/reader/sd/pii/S0306261917308954?token=DDC3EDD3E43F666-F24B6B7BDFD89A2191474-E8B6A77A4435EA4ED884FB6E83DC-3E8557D3B0AB598F3BEFFDCD316EE306.
[24] Andersen FM, Baldini M, Hansem LG, Jensen CL. Households'hourly electricity consumption and the peak demand in Denmark. Appl Energy 2017;208:607–19. https://www.sciencedirect.com/science/article/pii/S0306261917313776.
[25] Grandjean A, Adnot J, Binet G. A review and an analysis of the residential electric load curve models. Renew Sustain Energy Rev 2012;16:6539–65. https://www.sciencedirect.com/science/article/pii/S1364032112004820.
[26] Lund H, Mathiesen BV. Energy system analysis of 100% renewable energy systems - the case of Denmark in years 2030 and 2050. Energy 2009;34:524–31. https://www.researchgate.net/publication/223360918_Energy_system_analysis_of_100_renewable_energy_systems-The_case_of_Denmark_in_years_2030_and_2050.
[27] Mathiesen BV, Lund H, Karlsson K. 100% Renewable energy systems, climate mitigation and economic growth. Appl Energy 2011;88:488–501. https://www.forskningsdatabasen.dk/en/catalog/2174079006.
[28] Mathiesen BV, Lund H, Connolly D, Wnezel H, Østergaare PA, Möller B, Nielsen S, Ridjan IP, Sperling K, Hvelplund FK. Smart Energy Systems for coherent 100% renewable energy and transport solutions. Appl Energy 2015;145:139–54. https://www.sciencedirect.com/science/article/pii/S0306261915001117?via%3Dihub.
[29] Li Y, Yang Z, Li G, Mu Y, Zhao D, Chen C, Shen B. Optimal Scheduling of isolated microgrid with an electric vehicle battery swapping station in multi-steakeholder scenarios: a bi-level programming approach via real-time pricing. https://www.researchgate.net/publication/328062339_Optimal_scheduling_of_isolated_microgrid_with_an_electric_vehicle_battery_swapping_station_in_multi-stakeholder_scenarios_A_bi-level_programming_approach_via_real-time_pricing.
[30] Zotti, G.D., Pourmousavi, A., Morales, J.M., Madsen, H., Poulsen, N.K. Consumers'Flexibility Estimation at the TSO level for balancing Services. https://ieeexplore.ieee.org/document/8570785.
[31] Bunn J, Farmer ED. Comparative models for electricity load forecasting. New York: John Wiley; 1985. https://www.amazon.com/Comparative-Models-Electrical-Load-Forecasting/dp/0471906352.
[32] Ramanathan R, Clive RE, Granger WJ, Vahid-Araghi F, Brace C. Short-run forecasts of electricity loads and peaks. Int J Forecast June 1997;13(Issue 2):161–74. https://www.sciencedirect.com/science/article/pii/S0169207097000150.
[33] Amjady N. Short-term hourly load forecasting using time-series modeling with peak load estimation capability. IEEE Trans Power Syst NOVEMBER 2001;16(NO. 4). https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=932287.
[34] Matteo Maneraa *, Marzullo Angelo. Modelling the load curve of aggregate electricity consumption using principal components. Environ Model Softw 2005;20:1389–400. https://www.sciencedirect.com/science/article/pii/S1364815204002282.
[35] Aneiros Germán, Juan Vilar, Raña Paula. Short-term forecast of daily curves of electricity demand and price. Electrical Power and Energy Systems 2016;80:96–108. https://www.sciencedirect.com/science/article/pii/S0142061516000466.
[36] Dordonnat V, Koopman SJ, Ooms M, Dessertaine A, Collet J. An hourly periodic state space model for modelling French national electricity load. Int J Forecast 2008;24:566–87. https://www.sciencedirect.com/science/article/pii/S0169207008000988.
[37] Fan S, Hyndman RJ. Short-term load forecasting based on a semi-parametric additive model. IEEE Trans Power Syst FEBRUARY 2012;27(NO. 1). https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5985500.
[38] Moazzami M, Khodabakhshian A, Hooshmand R. A new hybrid day-ahead peak load forecasting method for Iran's National Grid. Appl Energy 2013;101:489–501. https://www.sciencedirect.com/science/article/pii/S0306261912004515.
[39] Lin Cheng-Ting, Li-Der Chou. A novel economy reflecting short-term load forecasting approach. Energy Convers Manag January 2013;65:331–42. https://www.sciencedirect.com/science/article/pii/S0196890412003160.
[40] Kim T-Y, Cho S-B. Predicting residential energy consumption using CNN-LSTM neural networks. Energy 2019;182:72–81. https://reader.elsevier.com/reader/sd/pii/S0360544219311223?token=B96F1059D4BD-91B221C538F91D4887902606E6D66357D33A27865B8AF5C92C2915F290-B8FBBD7F55076231A997139D3C.
[41] Martín-Rodríguez G, Cáceres-Hernández JJ. Modelling the hourly Spanish electricity demand. Econ Modell 2005;22:551–69. https://www.sciencedirect.com/science/article/pii/S0264999304000665.
[42] Pedregal Diego J, Trapero Juan R. Mid-term hourly electricity forecasting based on a multi-rate approach. Energy Convers Manag 2010;51:105–11. https://www.sciencedirect.com/science/article/pii/S0196890409003392.
[43] Yukseltan Ergun, Yucekaya Ahmet, Ayse Humeyra Bilge. Forecasting electricity demand for Turkey: modeling periodic variations and demand segregation. Appl Energy 2017;193:287–96. https://www.sciencedirect.com/science/article/pii/S0306261917301848.
[44] Boroojenia KG, Aminib MH, Bahramif S, Iyengara SS, Sarwatg AI, Karabasoglu O. A novel multi-time-scale modeling for electric power demand forecasting: from short-term to medium-term horizon. Electr Power Syst Res September 2016;142. https://www.researchgate.net/publication/307511698_A_novel_multi-time-scale_modeling_for_electric_power_demand_forecasting_From_short-term_to_medium-term_horizon.
[45] Filik ÜB, Gerek ÖN, Kurban M. A novel modeling approach for hourly forecasting of long-term electric energy demand. Energy Convers Manag 2011;52:199–211. https://www.sciencedirect.com/science/article/pii/S0196890410002803.
[46] Analyseforudsætninger til Energinet. The Danish energy Agency (In Danish), https://ens.dk/service/fremskrivninger-analyser-modeller/analyseforudsaetninger-til-energinet; 2018.
[47] NVV. Hva betyr elbiler for strømnettet?. report no. 74-2016, http://publikasjoner.nve.no/rapport/2016/rapport2016_74.pdf.
[48] Juul Nina, et al. StrategiesforChargingElectricVehiclesintheElectricityMarket. In: International journal of sustainable energy planning and management, 7.0; 2015. p. 2246–929. https://journals.aau.dk/index.php/sepm/article/view/1017.
[49] Optimized market participation of electric vehicles under uncertainty. http://pierrepinson.com/docs/Master_Thesis_Philipp_Andreas_Gunkel_s165394.pdf.