Demand Profiling and Demand Forecast Using the Active-Aware-Based Ensemble Kalman Filter

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Abstract. The concept of demand profiling is established in order to collect, analyse and develop the detailed knowledge of the consumption habits, either in domestic or non-domestic usage. In this paper the state representation of electrical signal is used as the profiling formula to model the diurnal (daily) and annual cycle demand trend of electricity consumption across the grid. The available demand dataset from the public domain is applied as the input for the profiling formula. The developed demand profile is further to be forecast and assimilated using the active-aware-based Ensemble Kalman Filter (EnKF). The resultant EnKF estimations may provide the assessment of nationwide demand within the energy network, thus consider the need for the present and future network reinforcement or upgrades. The ability of EnKF in forecasting the demand is presented, along with the limitations.

Keywords: Demand profiling · Demand forecast · Ensemble Kalman Filter · Data assimilation

1 Introduction

The national energy system is currently experiencing increasing stresses on demand and network load due to: variable heating in colder seasons; the addition of intermittent renewable generators; insufficient storage facilities. Furthermore, the needs to concentrate on balancing the electricity supply, the emission reduction targets, and the affordable operating costs are the current "energy-trilemma" problem [1]. The highest priority in optimising the renewable energy system, for instance, does not guarantee the security of energy supply due to the nature of renewable intermittency [2]. Therefore, various smart initiatives such as the introduction of disruptive technology [3] into the grid utility, decentralised energy distribution, and the high efficient low carbon power plants are deployed in mitigating the trilemma of the energy problem. To this end, the demand profiling concept are established after the inception of the 1950's Electricity Council Load Research and followed by the 1998 Electricity Pool Programme [4]. Such concepts are established to collect, analyse and develop the detailed knowledge of

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the consumption habits, either in domestic or non-domestic usage [4,5]. The electricity grid operator nowadays use demand profiling as the important strategy to plan the amount of electricity to be provided to the entire network. Additionally, demand profiling also illustrates the capacity trend of the electricity market, whether to power up a more responsive or expensive generation to meet the particular demand [6].

In addition to demand profiling, a good forecasting technique is required in order to provide the demand forecast for few days ahead. In this paper, the Ensemble Kalman Filter (EnKF) is applied in forecasting the demand profile. The EnKF justifies the calculation effort to demand forecasting and also aims to compute demand forecast based on the adequate amount of ensemble sizes for speedy delivery of forecast results. The resultant EnKF estimations may also provide the electrical inventory for assessment of nationwide demand and energy network upgrades.

The organisation of the paper is as follows. Section 2 presents the modelling of demand profile, the introduction and the formulation of EnKF. Section 3 demonstrates the results of demand profiling and EnKF forecast. Section 4 concludes.

2 Methodology

2.1 Modelling of Demand Profile

The electrical consumption representing the demand profile changes periodically with respect to time [7]. Such periodical trend or time series of the electricity data should have diurnal, $D(t)$, and annual, $A(t)$, periodicities [7]. The state representation of the consumed electrical signal can be generally expressed into the formula as follows:

$$X_i(t) = A\left(\frac{t}{T_1}\right) + D_i\left(\frac{t}{T_2}\right) + \varepsilon_i, \tag{1}$$

where $X_i(t)$ is the true state of electrical consumption at time t, $A(t)$ is the annual cycle function, $D_i(t)$ is the diurnal cycle function, T_1 is the annual periodicity that is 365 days, T_2 is the diurnal periodicity that is 24 h, t is the time variable sampled at hourly rate, ε_i is the signal noise, i indexes the types of consumers to be considered.

The $A(t)$ and $D(t)$ are used to describe trends of annual and daily demand profiles. The component of ε is the various influencing factors that affects the overall daily demand profiles. Typical influencing factors are: (1) Seasonal variations; (2) Building characteristics; (3) Weather and temperature effects; (4) Holiday effects; (5) Consumers consumption behaviour. The formula (1) is further used as the profiling formula in developing the complete annual trend of a demand profile representing ith consumer.

Depending the availability of the data, the $A(t)$ and $D(t)$ can be formulated using the real demand data in the public domain (e.g. [8]). In the case of insufficient data required to model the demand profile, the paper by [7] proposed an adaptive seasonal model based on the Hyperbolic tangent function (HTF) to model the electricity consumption for different types of consumers.

2.2 Ensemble Kalman Filter

Based on the historical UK demand reported in [8], the historical demand has shown fluctuations corresponding to different time periods. This is due to the influencing factor that affects the overall energy demand across the grid. Therefore short-term forecast and assimilation of energy demand are necessary. Several existing forecast methodologies are available but with present limitations. According to the author [9], both the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Autoregressive Integrated Moving Average (ARIMA) methods failed to forecast electricity demands with seasonal latent variables. Meanwhile, large numbers of Artificial Neural Networks (ANN) were proposed to handle seasonal variations but with potential drawbacks, where deseasonalising and detrending of pre-processed raw data is required in order to model seasonal trends accurately [10]. Additionally, the forecast using ANN is not always accurate and realistic [11].

Hence, a robust, active-aware-based forecasting mechanism is required to forecast the uncertain trends of the demand, either in long or short term forecast. In order to perform the demand forecast, EnKF is applied in this paper to forecast the demand.

EnKF was first introduced by Evesen [12] and is generally a Monte-Carlo based recursive filter approach for generation of an ensemble of model representations. An ensemble is actually a system representation through a random sampling of the system distribution [12]. EnKF is applied in sequential data assimilation and even a few ensemble members have the ability to exhibit large-scale covariance behaviour of a system considered [13].

2.3 EnKF Formulation

In this paper, formulations of EnKF by [2,14–18] are followed, with only key equations and parameters are outlined. Such EnKF formulation provides the foundation for the demand forecast and assimilation.

EnKF consists of two important steps, the forecast and analysis step. In the forecast step, as the true (actual) state is not always available, new ensemble is created in the state space by forecasting the ensemble mean as the best estimate of the state [14–16]. In other words, a new ensemble is created based on the realisations in each of the model state through the model dynamics (simulator). It is then reflected as the first observation of the actual system that will be incorporated into the model state in (2).

$$y_j^p = y^p + w_j, \tag{2}$$

where j indexes the ensemble member, y^p is the state vector of the model simulator, y_j^p is the new formation of a set of ensemble through the prediction of the model state y^p at ensemble member j, w_j is the model process noise. The superscript p denotes the *priori* state vector.

Instead of adding complex components to y^p, for simplicity the component of y^p can be formulated as:

$$y^p = \begin{bmatrix} m \\ d \end{bmatrix}. \tag{3}$$

In the simulation experiment, m is the model parameters of the energy consumption profile from the dynamical model (1). It is the profiling formula that describes the demand profile for ith consumers. As the component m describes the demand profile, m remain constant throughout the data simulation except the model process noise. This results in similar energy usage pattern from groups of consumers but with varied energy usages. The d is the model prediction of the energy consumption and changes with the simulation at every time step.

The input component of y^p can be further extrapolated as:

$$y^p = \left[m_{1,1}, m_{2,2},\ ...,\ m_{i,t},\ e_{1,1},\ e_{2,2},\ ...,\ e_{i,t}\right]^T. \tag{4}$$

The $m_{i,t}$ refers to the component m (3) of the dynamical model (1). The $e_{i,t}$ is the energy demand forecast that also corresponds to the component d. The i indexes the consumer and t is the time step.

As in line with [14], initial ensemble members of y^p are sampled from a normal distribution with the zero mean and standard deviation.

Using (2) and (4) new sets of priori ensemble y_j^p are created. Collections of forecasts y_j^p are stored into a matrix form Y^P to denote the collection of the *priori* ensemble:

$$Y^p = \left[y_1^p,\ y_2^p,\ ...,\ y_j^p,\ ...,\ y_{N_e}^p\right], \tag{5}$$

where N_e is the total number of ensemble member.

During the analysis step, new observations from measurement sets are established through ensemble representations. In order to obtain consistent error propagation the observations have to be considered as random variables [18]. The actual measurement is used as the reference and the random measurement noise is added to the measurement to obtain the perturbed observations [15,17,18]. In this paper, the actual measurement set d (also the model prediction) is perturbed using the ensemble representations, this later forms another set of ensemble of perturbed observations denoted by $d_{\text{obs},j}$:

$$d_{\text{obs},j} = d + v_j, \tag{6}$$

where v_j is the measurement noise at jth ensemble member.

Both y_j^p and $d_{\text{obs},j}$ are perturbed with model error: the process noise w with zero mean and covariance Q for Y^p and similarly, the measurement noise v with zero mean and covariance R for d, i.e. values w and v are assumed to be drawn from Gaussian distributions as $w \sim N(0, Q)$ and $v \sim N(0, R)$. The errors are very important to be defined in the EnKF, because without errors the system may be over-specified and no solutions resulting from EnKF propagations obtained [17].

The *priori* ensemble member y_j^p will be assimilated using the EnKF updating formula in order to obtain the updated *posteriori* ensemble y_j^u as follows:

$$y_j^u = y_j^p + C_Y H^T (H C_Y H^T + R)^{-1} (d_{\text{obs},j} - H y_j^p), \tag{7}$$

where H is the measurement operator that relates to actual state. C_p is the *priori* error covariance. R is measurement covariance error. The $d_{\text{obs},j}$ in this case corresponds to HY^p.

Using the formula (7), the assimilation process is achieved by updating y_j^p, assimilating y_j^p and $d_{\text{obs},j}$ by taking the mean of the perturbed observations $d_{\text{obs},j}$ as the actual observation. Each of the y_j^p ensemble member is updated to obtain y_j^u. The updated y_j^u is stored into a matrix form denoted as Y^u.

In order to examine the performance of EnKF, the root-mean-square error (RMSE) of the ensemble mean y_j^u from the actual state of the model [19] is used in this paper and is calculated as:

$$RMSE = \sqrt{\frac{1}{K} \sum_{k=1}^{K} \left(\overline{Y_k^u} - X_k\right)^2}, \tag{8}$$

where X denotes the actual state of electrical consumption from the dynamical model (1) and k is the model state variable.

3 Results

3.1 Numerical Simulation of Demand Profile

The half-hourly diurnal profiling data from the UK Elexon portal [20] is adopted in examining the diurnal seasonal demand profiles of spring, summer, autumn and winter correspondingly. The random perturbation of noises are generated to indicate the signal noises as the influencing factors. In this paper, the domestic household profile (out of eight clustered Profile Class) from the UK Elexon portal [20] is selected for further examination of the overall diurnal demand ($D_i(t)$). The clustered Profile Class represents large populations of similar demand profile within consumers [20]. On the other hand, the 2015 annual demand data from the UK National Grid portal [8] is extracted that corresponds to $A(t)$.

The $A(t)$ obtained from the portal [8] is converted to have identical temporal scale with $D_i(t)$. Those $D_i(t)$ will be 'stitched' together with $A(t)$ in order to form a resultant annual trend representing the overall household demand across the grid.

The analytical expressions of $A(t)$ and $D_i(t)$ based on (1) are to be further applied in EnKF for the demand forecast and assimilation process.

Figure 1 shows half-hourly diurnal energy consumption profile for domestic households with seasonal variations. Based on Fig. 1, it can be seen that a

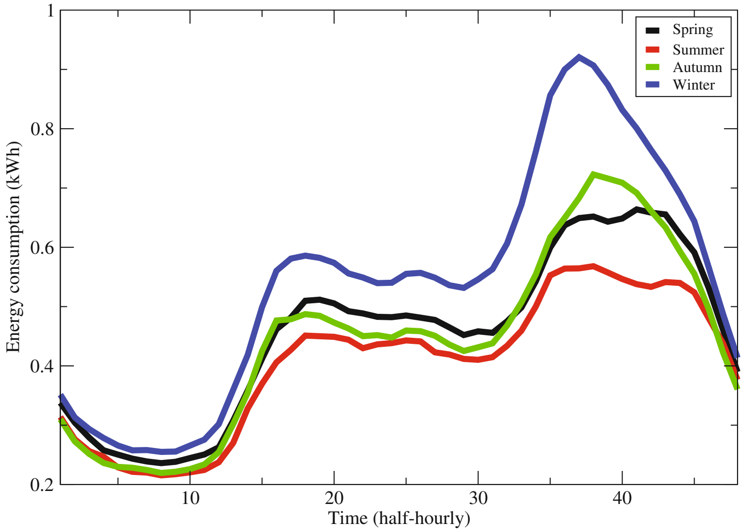

Fig. 1. Diurnal half-hourly energy consumption (demand) cycles for a domestic household.

household electricity consumption drops during the working hours and maximum demand occurs during the peak period (1700–1900). Additionally, the amount of energy consumption during the winter is much higher than other seasons due to the high amount of heating.

The plot from Fig. 1 is aggregated that further forms the half-hourly annual energy consumption as shown in Fig. 2, where $D_i(t)$ is stitched with $A(t)$ to form the complete annual household demand trend. Similarly, Fig. 3 shows the reduced temporal solution plot of Fig. 2, where the average annual-based daily energy consumption for the domestic household is plotted. The total estimated annual energy consumption is 4023kWh and such estimated value is similar to the overall household energy consumption usage as reported by the UK Department of Energy and Climate Change (DECC) [21]. Henceforth, the developed household energy demand trend is a good representation profile for the domestic household consumers.

3.2 EnKF Numerical Simulation

The EnKF simulation in this case involves short-term forecasting and assimilation of the energy consumption using the developed demand profile for the domestic household. The modelled profile of $X_i(t)$ from the dynamical model (1) is the observation that reflects the actual system that will be incorporated into the model state in (3). Since the household demand data is available, variable y^p in (3) contributes to direct model predictions (d) of the energy demand (based on (1) that formulates the household demand profile (m)).

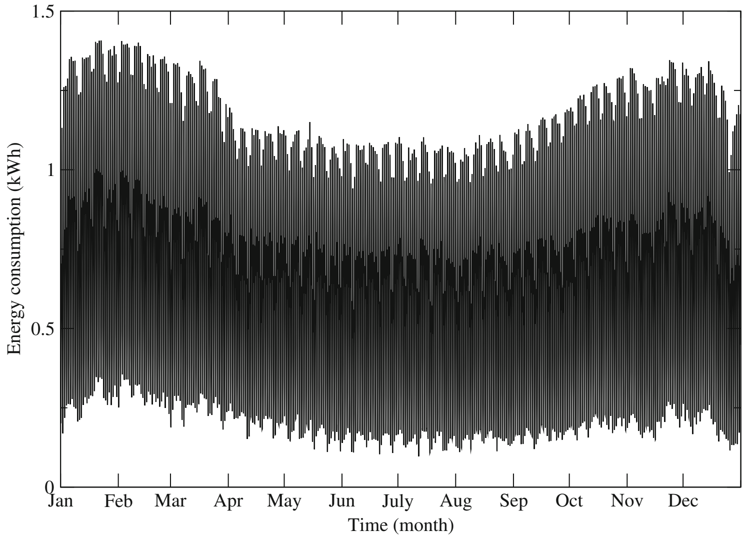

Fig. 2. Annual energy consumption (demand) cycles for a domestic household.

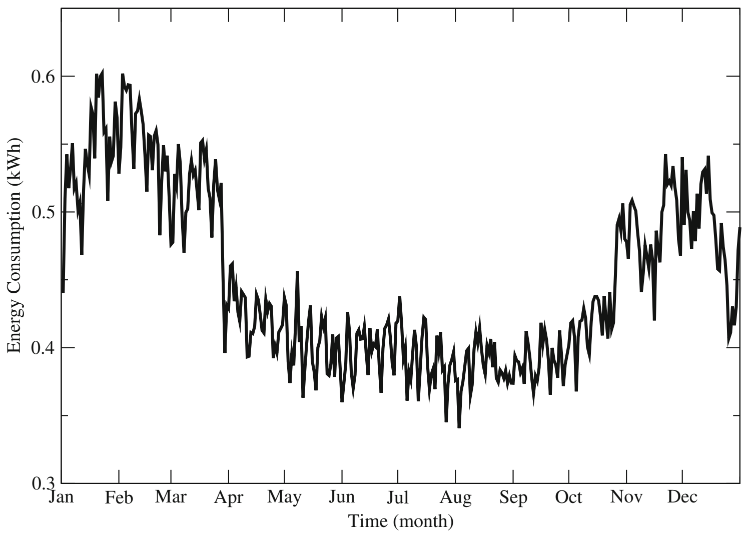

Fig. 3. Average annual-based daily energy consumption (demand) cycles for a domestic household.

The *priori* ensemble y_j^p is created using (2), where $j = 1, 2, ..., N_e$ denotes the ensemble member index and N_e is the total number of ensemble member. Initial ensemble members of y^p are intended to be drawn from a normal distribution with the mean and standard deviation $N(0, 20)$. Additionally, the model error

w is sampled from $w \sim N(0, 1)$. The measurement error, on the other hand, is sampled from $v \sim N(0, 0.5)$.

In the EnKF, the perturbed observation of demand data $d_{\text{obs},j}$ is based on the model prediction d using the formula (6). Different realisations are created (N_e = 10, 50, 100, 500, 1000) and propagated at every time steps. The Y^p in (5) is the collection of the *priori* ensemble y_j^p, which is assimilated along with $d_{\text{obs},j}$ and updated to form the *posteriori* ensemble (y_j^u) through (7).

The ensemble means of the energy demand with different realisations N_e are computed that allow comparison of the convergence in relation to the true (actual) state of the model. The RMSE of the propagated ensemble mean in relative to the actual model state is calculated using (8) in order to examine the robustness of EnKF with different realisations.

For feasibility purpose, total of five days temporal resolutions are adopted to demonstrate the EnKF propagation results. The five days plot with datasets of the actual energy demand and propagation of Y^u with different ensemble sizes is shown in Fig. 4. The figure shows that the larger the ensemble size, the better Y^u estimation converges towards the actual energy demand.

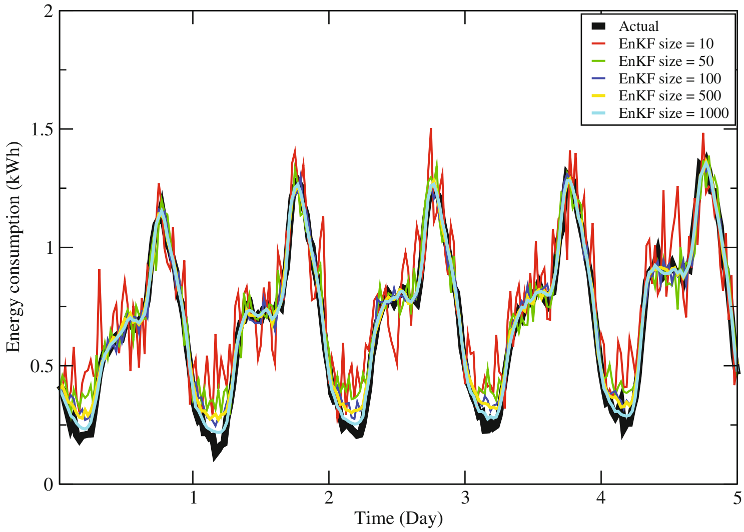

Fig. 4. Five days of household energy demand with different EnKF realisations.

The tabulated RMSE values corresponding to different EnKF realisations are shown in Table 1.

The RMSE values from Table 1 also indicate that the larger the ensemble size, the smaller the RMSE value, and thus the better the EnKF estimations. In this case, an ensemble of size 100 is sufficiently enough to provide accurate demand forecast with acceptable RMSE error.

Table 1. The RMSE value with different EnKF Realisations.

Number of ensemble (N_e)	RMSE value
10	0.180
50	0.087
100	0.050
500	0.035
1000	0.020

4 Conclusions

This paper presents the demand profiling using the available diurnal demand data in the public domain. A domestic household consumer is selected and to be further stitched together with the annual demand trend that is also available in the public domain that forms the annual energy demand for a household consumer. The state representation of electrical signal is used as the profiling formula to model the diurnal and annual demand trend of the domestic household. The profiled annual demand provides the realistic estimation that is comparable with the current UK domestic household energy usage. As there are available demand data in the public domain, this has added the flexibility and simplicity in modelling the overall energy demand with only a few parameters.

The resultant developed household demand profile is further applied in the active-aware-based EnKF field for demand forecasting and assimilation. The EnKF evaluation results demonstrate the capability and robustness of EnKF in forecasting and matching the energy demand, either in real-time or based on prior knowledge and historical records. However, as EnKF is a Monte Carlo type of data assimilation, the low EnKF realisation will result in poor forecast. The realisation of $N_e = 100$ in this example provides the sufficient convergence of EnKF propagations. For this reason, EnKF allows the convergence of data assimilations, on condition that the ensemble size selected is sufficiently large.

As the current EnKF application in this paper is demonstrated in a relatively simple model, the EnKF will however become complex when considering the individual demand profiles (for instance: office, hotel, school, supermarket, restaurant, stadium, and hospital). The nonlinearity in different profiles of consumers will arise and the identification of state variables, initial conditions and prior knowledge of the EnKF model are therefore necessary in order to provide the better demand forecast with minimised EnKF propagation errors.

References

1. E.ON UK. The energy trilemma (2016). https://www.eonenergy.com/for-your-business/large-energy-users/manage-energy/energy-efficiency/decentralised-energy-experts/The-energy-trilemma. Accessed 17 Feb 2016

2. Lau, E.T.: Quantification of carbon emissions and savings in smart grids. Phd thesis, College of Engineering, Design and Physical Sciences, Brunel University London (2016)
3. Plat, R., Williams, J., Pardoe, A., Straw, W.: A new approach to electricity markets - how new, distruptive technologies change everything. Technical report, Institute for Public Policy Research (2014)
4. Elexon. Load profiles and their use in electricity settlement (2013). https://www.elexon.co.uk/wp-content/uploads/2013/11/load_profiles_v2.0_cgi.pdf. Accessed 30 Apr 2016
5. DoE. Module 5: Energy assessment - demand analysis (2011). http://www.energy.gov.za/EEE/Projects/Building%20Energy%20Audit%20Training/Training%20Modules/Building%20Energy%20Auditing%20Module%205_final:pdf. Accessed 30 Apr 16
6. Energy Efficiency Exchange. Understanding your energy requirements (2016). http://eex.gov.au/energy-management/energy-procurement/procuring-and-managing-energy/understanding-your-energy-requirements/. Accessed 30 Apr 2016
7. Lau, E.T., Yang, Q., Forbes, A.B., Wright, P., Livina, V.N.: Modelling carbon emissions in electric systems. Energy Convers. Manage. **80**(59), 573–581 (2014)
8. National Grid. Data explorer (2016). http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Data-Explorer/. Accessed 01 May 2016
9. Sumer, K.K., Goktas, O., Hepsag, A.: The application of seasonal latent variable in forecasting electricity demand as an alternative method. Energy Policy **37**(4), 1317–1322 (2009)
10. Zhang, G.P., Qi, M.: Neural network forecasting for seasonal and trend time series. Eur. J. Oper. Res. **160**(2), 501–514 (2005)
11. Hippert, H.S., Pedreira, C.E., Souza, R.C.: Neural network for short-term load forecasting: a review and evaluation. IEEE Trans. Power Syst. **16**, 44–55 (2002)
12. Evensen, G.: Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte-Carlo methods to forecast error statistics. Geophys. Res. **99**(5), 10143–10162 (1994)
13. John, C.J., Mandel, J.: A two-stage Ensemble Kalman Filter for smooth data assimilation. Environ. Ecol. Stat. **15**, 101–110 (2008)
14. Almendral-Vazquez, R., Syversveen, A.R.: The Ensemble Kalman Filter - theory and applications in oil industry. Technical report, Norsk Regnesentral (2006). https://www.nr.no/en/nrpublication?query=/file/4334/Almendral_Vazquez_-_Ensemble_Kalman_Filter_-_theory_and_applications_i.pdf. Accessed 25 Jul 2015
15. Evensen, G.: The Ensemble Kalman Filter: theoretical formulation and practical implementation. Ocean Dyn. **53**(4), 343–367 (2003)
16. Gillijins, S., Barrero Mendoza, O.B., Chandrasekar, J., De Moor, B.L.R., Bernstein, D.S., Ridley, A.: What is the Ensemble Kalman Filter and how well does it work? In: Proceedings of the 2006 American Control Conference, Minneapolis, Minnesota, USA, pp. 4448–4453. IEEE (2006)
17. Jensen, J.P.: Ensemble Kalman Filtering for state and parameter estimation on a reservoir model. Master thesis, Department of Engineering Cybernetics, Norwegian University of Science and Technology, Trondheim (2007)

18. Nævdal, G., Johnsen, L.M., Aanonsen, S.I., Vefring, E.H.: Reservoir monitoring and continuous model updating using Ensemble Kalman Filter. In: SPE Annual Technical Conference and Exhibition, Denver, Colorado, USA, pp. 1–12. SPE (2003)
19. Anderson, J.L.: Localization and sampling error correction in Ensemble Kalman Filter data assimilation. Am. Meteorol. Soc. **140**, 2359–2371 (2012)
20. Elexon. Profiling - Average profiling data per Profile Class (regression data evaluated at 10-year average temperatures (2016). https://www.elexon.co.uk/reference/technical-operations/profiling/. Accessed 30 Apr 2016
21. DECC. Sub-national electricity and gas consumption statistics: analysis tool 2005 to 2014 (2015). https://www.gov.uk/government/publications/sub-national-electricity-and-gas-consumption-statistics-analysis-tool-2005-to-2009. Accessed 22 Mar 2016