Short-Term Load Forecasting at the Local Level using Smart Meter Data

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***Abstract*—Recent developments in active distribution networks, and the availability of smart meter data has led to much interest in Short-Term Load Forecasting (STLF) of electrical demand at the local level, e.g. estimation of loads at substations, feeders, and individual users. Local demand profiles are volatile and noisy, making STLF difficult as we move towards lower levels of load aggregation. This paper examines in detail the correlations between demand and the variables which influence it, at various levels of load disaggregation. The analysis investigates the forecasting capability of both linear and non-linear STLF approaches for forecasting local demands, and quantifies the forecast uncertainty for each level of load aggregation. The results demonstrate the limitations of several of the most commonly-used STLF approaches in this context. It is shown that, at the local level, standard STLF models may not be effective, and that simple load models created from historical smart meter data can give similar prediction accuracies. The analysis in the paper is carried out using two large smart meter data sets recorded at distribution networks in Denmark and in Ireland.**

***Index Terms*—Demand forecasting, smart grids, load management, forecast uncertainty, power demand.**

I. Introduction

Short-Term Load Forecasting (STLF) is the forecasting of electrical demand over periods from several hours to a week ahead. The forecasting of electrical demand is considered to be critical for power system operation, particularly for energy balancing, energy market trading and management of system reserves [1], [2]. Most of the previous literature in the STLF area to date focuses on large-scale aggregated loads, such as the aggregated electricity demands for entire countries, or regions, for transmission system applications.

However, recent developments such as active distribution networks and the large-scale integration of distributed energy resources have led to significant interest in applying STLF at a more local, disaggregated level. A number of authors have investigated the forecasting of demand at each substation in the network, or even at the individual feeder or end-user level [3]–[10]. Moreover, the recent availability of smart metering data provides much more detailed information on electricity end-use than was available before.

STLF has been carried out at the local level for various applications. These include: prediction of user load profiles for demand side management, e.g. [4], [5]; energy storage optimisation (i.e. selection of optimal charge/discharge times and rates [6]; electric vehicle integration [8]; and microgrid and virtual power plant applications [7], [11]. In addition, STLF at the local level is used to provide load estimates to enhance the accuracy of distribution system state estimation in [9], [12]–[14]. Various modelling approaches have been applied for STLF of local, disaggregated loads, including sophisticated forecasting techniques based on linear and non-linear predictive models, [4]–[9].

STLF is particularly challenging at the local level, since disaggregated demands are more volatile and noisy [10]. This paper demonstrates that standard techniques for STLF generally do not perform well at lower levels of aggregation. In addition, this paper quantifies some of the limitations of standard STLF approaches for forecasting of local demands, and defines the level of accuracy that is achieved at each level of load disaggregation: substations; feeders; and individual end-users. The results suggest that, at lower levels of aggregation, very simple demand models (e.g. assuming demand is equal to the demand in the same hour of the previous day), can be at least as effective as sophisticated STLF approaches based on linear or non-linear predictive models. In this context, this paper provides several novel contributions:

- A detailed assessment of the correlations between electrical demand and the variables which influence it, at each level of aggregation. This assessment is carried out using a data set comprised of smart meter demand recordings and local weather data from residential customers in two European countries.
- An analysis of the performance of some of the most commonly-used STLF methods, and their limitations when applied to local, disaggregated demands.
- A discussion of the implications of these results for typical power system applications.

The authors kindly acknowledge the support of the European Commission projects on Marie Sklodowska-Curie researcher mobility action (FP7-PEOPLE-2013-COFUND), the SmartHG research project (FP7-ICT-2011-8, ICT-2011.6.1), and the Spanish Ministry of Economy and Competitiveness project RESmart (ENE2013-48690-C2-2-R).

II. Methodology

A. Analysis of Demand Correlations

The variables which affect demand in the short-term typically fall into three categories: time-related (e.g. day, hour of day, and whether or not the day is a normal working day); historical (e.g. previous hour demand, previous week equivalent hour demand, previous 24 hour average); and weather-related (temperature has by far the greatest influence, but other weather factors such as humidity/precipitation, solar irradiation, and wind can also have effects).

Regression techniques are widely employed to analyze the relationship between variables in models for load forecasting [15]–[17]. A commonly-used measure for the strength of the linear relationship between two variables is Pearson's correlation coefficient:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{1}$$

where x_i and y_i with $i = 1, \ldots, n$ are values of the dependent and independent variables, respectively. The parameters $\bar{x}$ and $\bar{y}$ represent the average values of the dependent and independent variables considered in the analysis. The correlation coefficient may vary between 1 (perfect positive correlation) and -1 (perfect negative correlation). Values near 0 are a result of a weak dependence between the analyzed variables. The influence of the aggregation level on the correlation between the demand and the above-mentioned variables is analysed and the results are shown in Section III-B. The outcome of the analysis is used for the design of suitable models for STLF.

B. Short-Term Load Forecasting (STLF) Models

In order to carry out STLF, a model of the electrical demand is created using some or all of the variables discussed above. A range of linear or non-linear predictive techniques can be applied to the STLF problem. Several approaches are applied in this paper:

1) Naive Model: A "naive" model is a credible forecast which captures the salient features of the load profiles of interest, but does not have any forecasting skill [2]. In this paper, the Naive Model simply assumes that the demand at each time period will be equal to the demand at the same time period in the previous equivalent day[1].

2) Load Shape Model: Load shape, or time-of-day models describe the load $z(t)$ at each time instant t over the forecast duration T:

$$z(t), \quad t = 1, 2, ..., T \tag{2}$$

The time-of-day model is created as a set of demand curves based on historical demand recordings. The load shape used in the model usually varies according to season, and various curves can be created for special conditions, e.g. dry days, wet days, holidays etc. Alternatively, the load shape model can be expressed as:

$$z(t) = \sum_{i}^{N} \alpha_i(t) f_i(t) + e(t), \quad t = 1, 2, ..., T \tag{3}$$

where $f_i(t)$ is the time function representing the typical load shape, $\alpha_i(t)$ are coefficients which represent the recent demand behaviour, which are fitted at regular intervals using linear regression, and $e(t)$ represents the noise, or error.

The Load Shape Model used in the analysis below is the simple demand curve in (3) based on previously recorded data, where separate load shape models are used for each season, and for working/non-working days.

3) Linear Autoregressive Models: The most commonly-used linear predictive model in STLF is the Auto-Regressive Moving Average model. The demand profile can be expressed as:

$$z(t) = y_{tod}(t) + y(t) \tag{4}$$

where $y_{tod}(t)$ is the time-of-day component, in the form of a load shape model, such as (3). The load residual component $y(t)$ represents the deviation due to weather and other random correlation effects, and can be modelled as an ARMA process:

$$y(t) = \sum_{i=1}^{p} a_i\, y(t-i) + \sum_{i=1}^{q} b_i\, u(t-i) + w(t) \tag{5}$$

where p is the order of the Autoregressive (AR) model, q is the order of the Moving Average (MA) model, and $w(t)$ is a zero-mean white noise component representing random load fluctuations. The parameters a_i and b_i are identified by fitting the model to recorded demand and weather data [1].

4) Non-Linear Autoregressive Models: Non-linear STLF models, such as those based on Neural Networks (NNs) have been widely used in the literature. A recursive NN approach can be applied for STLF, and the analysis in this paper uses the Non-linear Auto-Regressive eXogenous (NARX) model outlined in [9]. The model is expressed as:

$$y_{t+1} = F(y_t, y_{t-1}, ..., y_{t-do}, \;\; u_t, u_{t-1}, ..., u_{t-di}) \tag{6}$$

where the next value of the output signal (e.g. the kW load), y_{t+1}, is regressed using previous load measurement values y_t, $y_{t-1}, \ldots$ and input signals u_t, $u_{t-1}, \ldots$, (e.g. weather, time-related and historical load variables). The function F represents a neural network, where the weights for each connection in the network are trained in MatLab using the Levenberg-Marquardt back-propagation algorithm. The number of time delays in the input and output layers are denoted di and do respectively. These can be adjusted to allow for different forecasting horizons, e.g. hour-ahead, day-ahead etc. For example, to calculate the 24 hour-ahead forecast, y_{t24}, for a given node (assuming that all of the required variables are available from the previous 24 hours), (6) is re-formulated as:

[1] The "equivalent" day here refers to the fact that the data is separated into working and non-working days. For instance, the previous equivalent day for a typical working Monday is taken as the previous Friday (working day) rather than the day before, Sunday (non-working day).

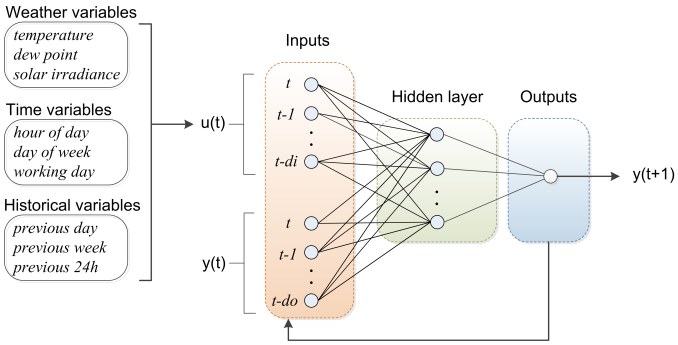


Fig. 1. Structure of the Non-linear AR load forecasting model.

$$y_{t24} = F(u_{t-24}, ..., u_{t-48}, \quad y_{t-24}, ..., y_{t-48}) \qquad (7)$$

The structure of the proposed Non-linear AR model for forecasting net substation demand is illustrated in Fig. 1. The input signals u_t are specified as follows:

- three weather forecast variables[2]: temperature and dew point (both measured in °C), and solar irradiance in W/m^2.
- three time-related variables: these consist of variables for hour of day $H_t = [1, 2, ..., 24]$, day of the week $D_t = [1, 2, ..., 7]$, and a variable $W_t = 1$ or 0, where 1 indicates a working day, and 0 indicates a non-working day, such as a weekend or bank holiday.
- three historical demand variables which have a strong correlation with the demand profile: the recorded demand at the same hour of the previous day, the same hour of the previous week, and the previous 24-hour average demand level.

The average time required to train the Non-linear AR model with one entire year of input data was around 60 seconds (using a standard PC with a 2.6 Ghz microprocessor). The best results were obtained using a feed-forward NARX model, comprised of an input layer with 9 neurons (one for each input variable), one hidden layer with 10 neurons, and an output layer with one neuron.

III. Analysis and Results

A. Description of Smart Meter Data Sets

In this paper, two large data sets comprised of smart meter recordings were used to analyse the correlations between demand and the variables which influence it, and for carrying out the load forecasting. The first data set is taken from the EU project "SmartHG" [18]. Smart meter demand data was obtained from 1,600 customers from a Danish distribution network operator for a continuous period of 24 months during 2012-2014, at a resolution of 1 hour. The corresponding local weather forecast data (including typical 24-hour ahead forecast errors) were obtained by request from the Danish Meteorological Institute [19].

[2]Other weather variables, such as precipitation and wind speed were recorded and analysed, but it was found that these did not have a significant impact on the demand.

The second data set is taken from the Irish Smart Metering Electricity Customer Behaviour Trials [20] which recorded half-hourly smart meter demand from 6,500 customers over a period of 18 months at various distribution network locations in Ireland. Corresponding weather data was requested from the Irish Meteorological Service [21]. In the paper, these data sets are subsequently referred to as the "Denmark" and "Ireland" data sets, respectively. Both data sets were split in a 50:50 ratio into "model training" data and "model validation" data, so for the Denmark data set there were 12 months of training data and 12 months of validation data (and 9 months each in the case of the Ireland data set). The STLF models are designed and trained using the training data only, and all forecasting results shown are calculated using the validation data only. Only the results from smart meter demand data recorded from residential users are given in the paper, and only results for working days are included (weekends and non-working days due to holidays are removed from the data set).

The following analysis examines STLF at four different levels of demand aggregation:

- **(i)** Primary HV/MV substations (hundreds to thousands of customers)
- **(ii)** Secondary MV/LV substations (few hundreds of customers)
- **(iii)** LV feeder level (few to tens of customers)
- **(iv)** End-user level (single customer)

Fig. 2 shows a sample of the day-ahead predictions from the linear AR model described in Section II-B. It is clear that STLF accuracy decreases at low levels of aggregation. This effect is expected due to the higher volatility and variability of disaggregated loads. In Section III below, detailed results are provided for each STLF model at all levels load aggregation.

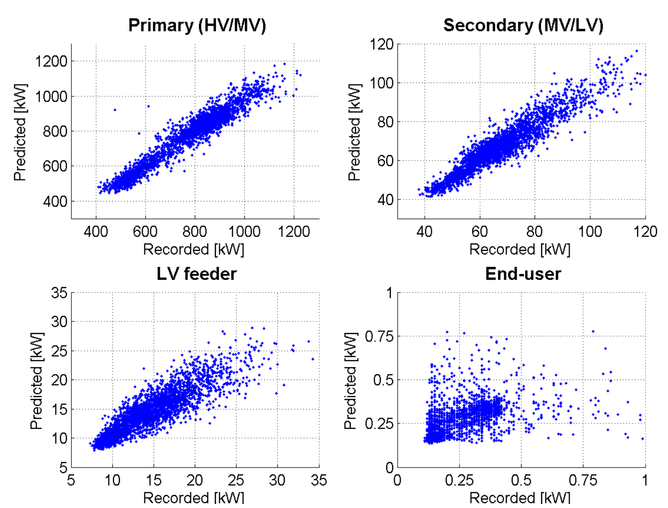


Fig. 2. Sample of results for day-ahead forecasting of hourly residential demand profiles at various levels of load aggregation.

B. Analysis of Demand Correlations

The correlation between the demand and the variables affecting the demand was analysed on a weekly basis. Smart meter and local weather data have been used to study the influence of the aggregation level on the correlation coefficients. The main findings (see Fig. 3 for the results) are:

- A weak correlation between the demand and the analysed variables has been found on end-user level. Inferior predictions can be expected with a linear regression model.
- The correlation with the previous day equivalent hour demand, previous week equivalent hour demand and hour of day increases with the aggregation level. A relatively low correlation has been observed for previous 24 hour average and temperature at all aggregation levels.

The analysis on an annual basis shows strong correlations with the temperature (negatively correlated) and the previous 24 hour average demand.

C. Comparison of Results from STLF Models 1-4

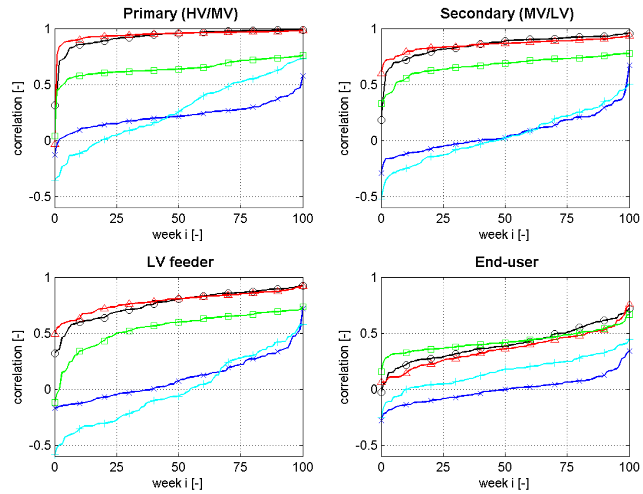
The results of the demand correlation analysis show that the correlations between the demand and the variables which affect it (i.e. weather, time and historical) are significantly lower at the local level. This suggests that the predictability of demand at lower levels of aggregation (e.g. at individual users, or small groups of users) will also be lower. In the following section, all four STLF models described in Section II-B are applied to both the Denmark and Ireland smart meter data sets for day-head (i.e. 24 hours-ahead) demand forecasting, and the results are calculated at each aggregation level. The aim of this analysis is to investigate which STLF models perform best, and what accuracy can realistically be achieved at each level of aggregation. The prediction error is expressed as the Mean Absolute Percentage Error (MAPE), given by:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{A_t - F_t}{A_t}\right| \quad (8)$$

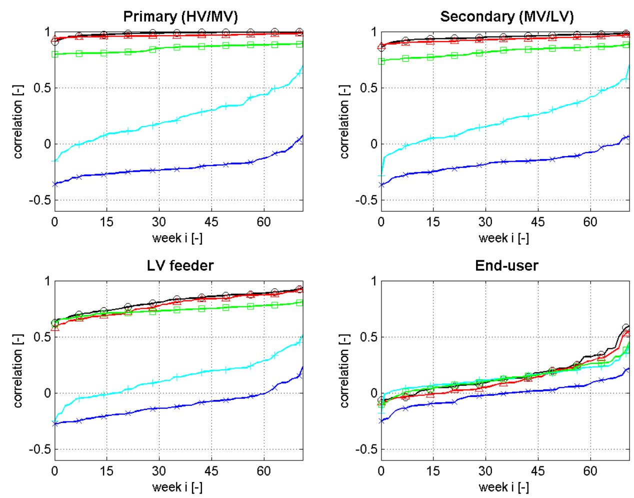
where A_t and F_t are the actual and predicted demands recorded at each time step t, and T is the total number of time steps in the validation data set (12 months in the case of the Denmark data set, and 9 months for the Ireland data set).

Figs. 4a and 4b show the MAPE from each of the STLF models 1-4 described in Section II-B, for the Denmark and Ireland data sets, respectively. It is clear that STLF accuracy decreases at low levels of aggregation, reflecting the pattern shown in the demand correlation analysis. The pattern is similar for both data sets, with <5% prediction errors achieved at the Primary (HV/MV) substations and decreasing accuracy at each subsequent aggregation level, with all STLF models 1-4 showing very high MAPE values (20-30%) at the individual end-user level.

The results in Fig. 4 show that at the Primary (HV/MV) and Secondary (MV/LV) substations, the more advanced STLF models (3 and 4) clearly outperform the simpler models (1 and 2). However, at the local level (LV feeders and individual users), the STLF models 2-4 do not offer any clear improvement over the Naive Model (1), indicating that the application of more advanced STLF models is of no benefit in this case.



(a)

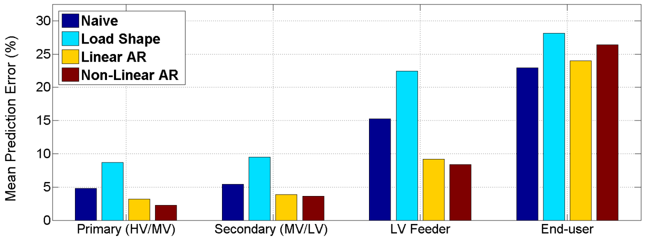


(b)

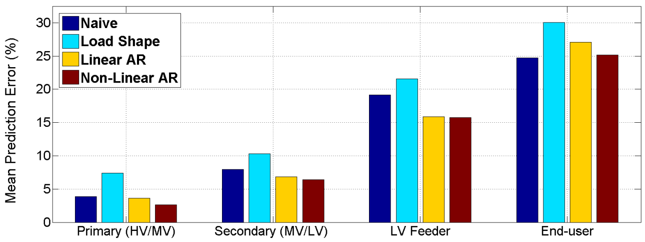
Fig. 3. Sorted correlation coefficients on a weekly basis for previous day equivalent hour demand (triangles), previous week equivalent hour demand (circles), previous 24 hour average (x), temperature (+) and hour of day (squares) at various levels of load aggregation: a) DENMARK data set; b) IRELAND data set.

D. Distribution of Load Forecasting Errors

The results in Fig. 4 provide the *mean* prediction errors at each level of aggregation. In order to provide results illustrating the *distribution* of the load forecasting error, boxplots of the prediction errors are given for each month of the year for the Denmark site, Fig. 5. The results show that at all levels of aggregation the prediction accuracy is relatively consistent across the year, but with higher forecast errors in the summer (low demand) months. It is also clear that at the LV feeder (Fig. 5c) and individual user (Fig. 5d) level the errors are much more widely distributed, with large outlier values occurring.

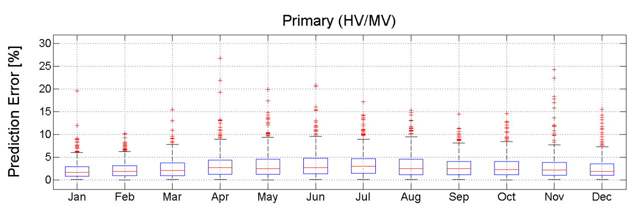


(a)

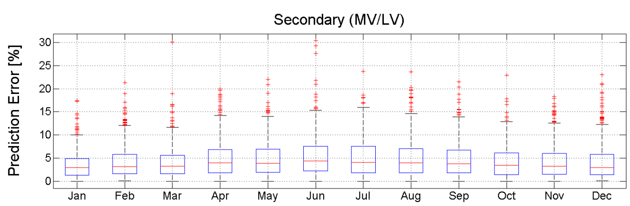


(b)

Fig. 4. Comparison of STLF model mean prediction errors, at various levels of load aggregation: a) DENMARK data set; b) IRELAND data set.



(a)



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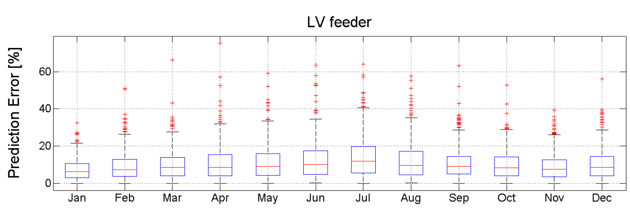
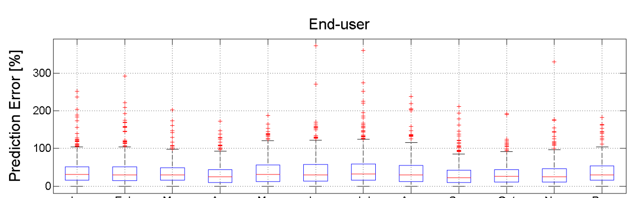


(c)



(d)

Fig. 5. STLF error boxplots by month, using non-linear AR model at each level of aggregation: a) primary substation; b) secondary substation; c) LV feeder; d) individual user. Outlier values are indicated by crosses (+).

E. Variation of Errors with Forecasting Horizon

The forecasting errors obtained vary according to the forecasting horizon used in the model. The demand prediction is made using the Non-linear AR model described in Section II-B and the forecasting horizon h is varied from 1 hour ahead to 48 hours ahead. In addition to providing a point estimate of the predicted demand at each time instance, a probabilistic estimate is made, which takes into account the historical error distribution of the demand forecasting. The demand forecasting error vector at forecasting horizon h is given by:

$$\mathbf{e}_h = A_t - F_t \qquad for \;\; t = 1, 2, ..., T \tag{9}$$

where T is the total number of available actual and forecasted data points in the data set. This demand forecasting error varies according to the demand forecasting horizon. In order to create confidence intervals for each forecasting horizon from 1 hour ahead to 48 hours ahead, the *percentile errors* for each error vector $\mathbf{e}_1$ to $\mathbf{e}_{48}$ are calculated. For example, the 90% confidence interval for a single point demand forecast at 48 hours ahead y_{t48} is given by:

$$C_{90} = -\pi_{95} \leq \mathbf{e}_{48} \leq \pi_{95} \tag{10}$$

where π_{95} is the 95^{th} percentile of $\mathbf{e}_{48}$. The advantage of using a non-parametric approach with percentiles is that the method is independent of the probability distribution of the demand forecasting errors. A sample of the results at the secondary (MV/LV) substation level are shown in Fig. 6 for the Denmark data set.

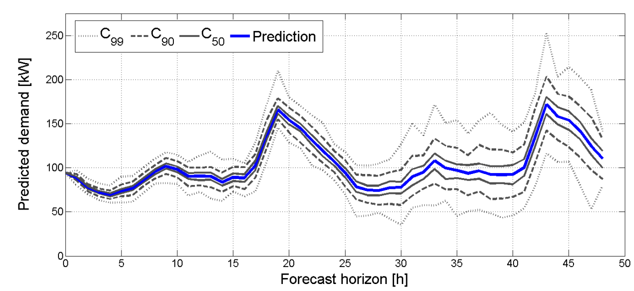


Fig. 6. Load forecasting at the secondary (MV/LV) substation level, where the forecasting horizon is varied from 1 hour ahead to 48 hours ahead. Confidence intervals are shown at 50% (solid lines), 90% (dashed lines), and 99% (dotted lines).

IV. Discussion and Conclusions

The analysis in Section III-B of this paper showed that, at the local level of LV feeders and individual users, the correlations between demand and the influencing variables become much weaker. Accordingly, there was a significant decrease in STLF accuracy as we moved towards lower levels of demand aggregation. The results of the forecasting in Section III-C showed that the prediction capability of commonly-used STLF approaches based on linear or non-linear predictive models is very limited at the local level, and that such approaches are not more effective than simple time-of-day or naive models.

To the authors' knowledge, this is the first research paper to attempt to quantify this effect of disaggregation on demand prediction using smart meter data. It was demonstrated in Section III using both data sets that high levels of prediction accuracy (e.g. $<5\%$ average MAPE day-ahead) could be achieved at the primary and secondary substation aggregation levels, if appropriate STLF models were used. The Non-linear AR model described in Section II-B was demonstrated to be particularly effective for this application. However, at very low levels of aggregation (LV feeders and individual users), it was shown that all forecasting methods had inferior results, e.g. $>25\%$ average MAPE, which is unsuitable for most practical applications. It should be noted that the performance of a given STLF model is difficult to fully assess using a single metric, such as the widely-used MAPE. Alternatives to MAPE, based on probabilistic metrics could be applied, e.g. in [10] the authors propose new performance metrics designed for use with noisy, volatile end-user demands. While the model accuracy in any energy forecasting approach is important, other aspects should also be considered, e.g. computation time, ease-of-use, ability to deal with bad data, and the need for periodic updating/re-tuning of the model.

The results in Section III have important implications for various smart grid applications, such as co-ordination of demand management in buildings, and optimisation of local energy storage devices. If the actual predictability of local demand profiles is poor due to load volatility, this high level of demand uncertainty needs to be considered when developing and implementing energy management algorithms. The active management of energy resources in the distribution systems creates more variability in demand patterns, both temporally and spatially. This creates the need for developing new load forecasting approaches that are more suitable for the smart grid environment.

Future load forecasting methods will need to be probabilistic, e.g. producing ranges of values rather than point forecasts, in order to better model such demand uncertainties, Fig. 6, Section III-E. Additionally, there will be much more interaction between demand, embedded variable generation, and electricity prices (e.g. variable prices will affect demand, and variable demands will affect prices). Therefore, load forecasting, variable generation forecasting and electricity price forecasting will need to be fully integrated, i.e. considering all of these interactions and feedback loops. Data from smart meters can allow us to understand these changes in demand patterns in more detail and help produce more useful forecasts. Analysing large sets of smart meter data effectively is a particular challenge. For instance, the Ireland data set used in this paper contained more than 500 million individual data points to be analysed.

Future work will investigate local-level forecasting of other load sectors, such as commercial and industrial demands, and will investigate the impact of embedded variable generation (e.g. rooftop solar panels) and flexible demands on the load forecasting. Additionally, further work will demonstrate the impacts of local demand forecast uncertainty on power system applications such as optimisation of charge and discharge cycles for battery or electric vehicle charging, co-ordinated demand management in buildings, and microgrid operation.

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